FUZZY EXPERT SYSTEMS: A MORE HUMAN-BASED APPROACH FOR SENSORIAL EVALUATION OF COFFEE-BEAN ATTRIBUTES TO DERIVE QUALITY SCORING

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I have submitted this thesis in partial fulfillment of the requirements for the degree of Master of Science

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Fuzzy Expert Systems: A more human-based approach for sensorial evaluation of coffee-bean attributes to derive quality scoring

A Thesis in

Applied Computer Science

by

Javier A Livio

Submitted in Partial Fulfillment
Of the Requirements
For the Degree of

Master of Science

November 2016

I have submitted this thesis in partial fulfillment of the requirements for the degree of Master of Science

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ABSTRACT

In the coffee industry, “cupping” is the process of sensorial evaluations of coffee beans, also known as Sample Evaluation. This process is done for three major reasons: to determine the actual sensory differences between coffee samples, to describe the flavors of the samples, and to determine preference of product. In totality, cupping targets the measurement of the coffee’s quality related to fragrance, taste, and appearance which are expressed with a final numerical score. When cupping, the expert judge writes down the individual components’ scores (fragrance, aftertaste, acidity, body, etc.) and ranks their intensities for reference. Despite the fact the cuppers are using natural language statements in their judgment, they are required to use numerical values to evaluate the coffee bean attributes. Fuzzy systems allow an intuitive way of representing the judge’s knowledge, by linguistically modeling the judge’s perception of the coffee’s attributes for sensorial evaluation of coffee-bean attributes to enhance the *Specialty Coffee Association of America* cupping process to derive quality scoring when grading specialty coffees. With a fuzzy expert system the judge’s perception could be better assisted with a collection of linguistically expressed terms instead of numbers (complementary terms acting as shapers of the coffee bean’s attribute score’s gradation of meaning).

Keywords: Expert systems, Fuzzy Sets, Fuzzy Reasoning, Coffee Sensorial Evaluation, Mamdani-Style Engine, AI Cupper, Specialty Coffee Association of America

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ACKNOWLEDGEMENTS

My advisor and committee members: Dr. Rania Hodhod, Dr. Alfredo Perez, Dr. Wilfredo Flores, and Dr. Shamim Khan

Specialty Coffee Association of America (SCAA)

My wife Ines and our two kids, Karen and Sebastian

Dr. Noah Dormady

Salvador and Rachel Arredondo

My dearest sister, Margaret

Chapter 1. Introduction

1.1 Problem Statement

In the United States alone specialty coffees represent 37% volume share in an estimated marked of the coffee at $30 to $32 billion dollars. In addition, it is estimated that more than 125 million people are directly influenced by coffee farming in both rural and developing regions (SCAA, 2012). There are two primary types of coffee, Arabica and Robusta being the Arabica type, which grows best at higher elevations in tropical or sub-tropical climates, the most used in the specialty coffee.

The absence of defects (bitterness, harshness, sourness) in coffee beans is a paramount, according to SCAA (Specialty Coffee Association of America) protocols, a single sample (coffee bean) is cupped (judge) at least fifteen times by professional judges (cuppers) trained to identify flaws. A skilled coffee judge should be able to detect any defects or other off-putting flavor or aromas. The SCAA remarks that "The purpose of this cupping protocol is the determination of the cupper's preference" (SCAA, 2013, p. 2). This indicates that it is up to the cupper (the domain expert) to determine by preference the quality of the coffee beans deemed to be graded as specialty coffee.

The main purpose of this project research is to design and develop a fuzzy expert system to capture and preserve the irreplaceable human expertise of the coffee judges and capitalize on it. Eventually, once the expert system becomes part of the coffee attributes' evaluation, it could alleviate the sensorial stress to which the judge gets expose while sensing and perceiving both, flavors and aromas to ascertain with numbers the coffee's quality. In other words, as the cuppers perform their sensorial evaluations the previously represented knowledge will work on their behalf.

1.2 Sensorial Evaluation of Coffee Beans (SCAA Protocol)

The SCAA has designed the cupping protocol providing guidelines toward the testing of the coffee samples. This standard protocol for "Sample Evaluation" remarks three areas: to determine the actual

sensory differences between samples, to describe the flavor of samples and to determine preference of products (SCAA, 2013, p. 6) Cupping targets the measurement of the coffee's quality which is expressed with a final numerical score. Cuppers use a rubric , the SCAA's Cupping Form which provides means of recording important flavor attributes rated on a sixteen point scale representing level of quality in quarter points increments between numeric values from 6 to 9 (SCAA, 2013, p. 4). This numerical scores support the cupper's previous experiences in determining his or her preferences, knowing that "coffees that receive higher scores should be noticeable better than coffees that receives lower scores" (SCAA, 2013).

In this thesis we have used Fuzzy Set theory to solve a real-world problem that is the specialty coffee beans' sensorial evaluation to determine their quality grading. The proposed solution resulted in the design and development of the AI Cupper, The Artificial Intelligent Coffee Judge (see AI Cupper Logo in Figure 1.2.1).

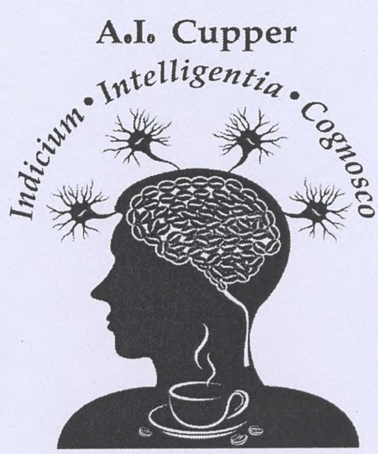


Figure 1.2.1: AI Cupper's Logo

The AI Cupper presents a more human-based approach for sensorial evaluation of coffee-bean attributes to derive quality scoring. The system allows an intuitive way of representing the judge's knowledge, by linguistically modeling the judge's perception of the coffee's attributes for sensorial

evaluation of coffee-bean attributes to enhance the SCAA's cupping process to derive quality scoring when grading specialty coffees.

1.3 Mamdani-style Fuzzy Inference

The Mamdani-style fuzzy inference or Mamdani method was presented in 1975 by Professor Ebrahim Mamdani of the University of London. Professor Mamdani built one of the first fuzzy systems to control a steam engine and boiler combination. He applied a set of fuzzy rules supplied by experienced human operators (Negnevitsky, Artificial Intelligence a Guide to Intelligent Systems - Thrid Edition, 2011, pp. 106-107). Mamdani is widely accepted for capturing expert knowledge. This method "allows us to describe the expertise in a more intuitive, more human-like manner" (Negnevitsky, Artificial Intelligence a Guide to Intelligent Systems - Thrid Edition, 2011).

Despite the fact that Mamdani requires us to find the centroid of a two dimensional shape by integrating across a continuously varying function, this process is not computational efficient but nevertheless is probably the most popular one because in practice works really well with a reasonable estimate calculating over a sample of points, see Table 1.3.1 describing Mamdani's process. The centroid or center of gravity used by Mamdani, is a technique with several desirable properties. First the defuzzified values tend to move smoothly around the output fuzzy region, in other words changes in the fuzzy set topology from one model frame to the next usually result in smooth changes in the expected value. Second it is relatively easy to calculate and third it can be applied to both fuzzy and singleton (a fuzzy set with a membership function that is unity at a single particular point on the universe of discourse and zero everywhere else) output geometries (Cox, 1999, pp. 308-310)

Table 1.3.1 Mamdani-style Fuzzy Inference steps

Step	Description
Fuzzify Input Variables	Apply fuzzy logic to coffee bean attributes scores. Determine the degree to which these inputs belong to each of the appropriate fuzzy sets
Apply Fuzzy Operator	Take the fuzzified inputs and apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function
Apply Implication Method	Now the result of the antecedent evaluation can be applied to the membership function of the consequent
Apply Aggregation Method	The process of unification of the outputs of all rules. We take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. The input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable
Defuzzification	The last step in the fuzzy inference process is defuzzification. Fuzziness helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp value. The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number.

1.4 Our Contribution

In the current cupping process, crisp numeric values are used to represent coffee-bean's attributes perceived by the cupper; for example, Aroma equal 7.5 or Acidity equal 7 as the SCAA cupping protocol indicates, and so forth (SCAA, 2013, p. 2). With our proposed expert system, the experience and knowledge of coffee experts is capitalized to the point that the cuppers will focus just on expressing with linguistic terms their findings.

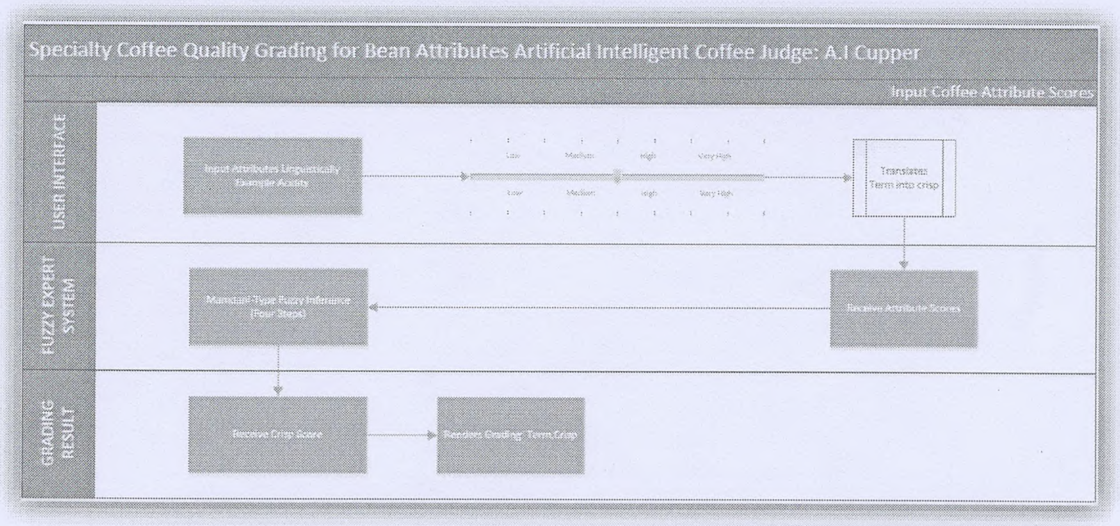


Figure 1.4.1: Coffee Attributes linguistically expressed for the Acidity attribute

Figure 1.4.1 shows the user interface (UI) rendering the linguistic terms associated with the coffee bean attributes (Acidity). Figure 1.4.2 shows the user interface of the current expert system. The interface visually renders with a slider the linguistic terms representing the "Acidity" coffee bean attribute, it receives the judge's selected input and translates it into a crisp numeric value never seen by the cupper.

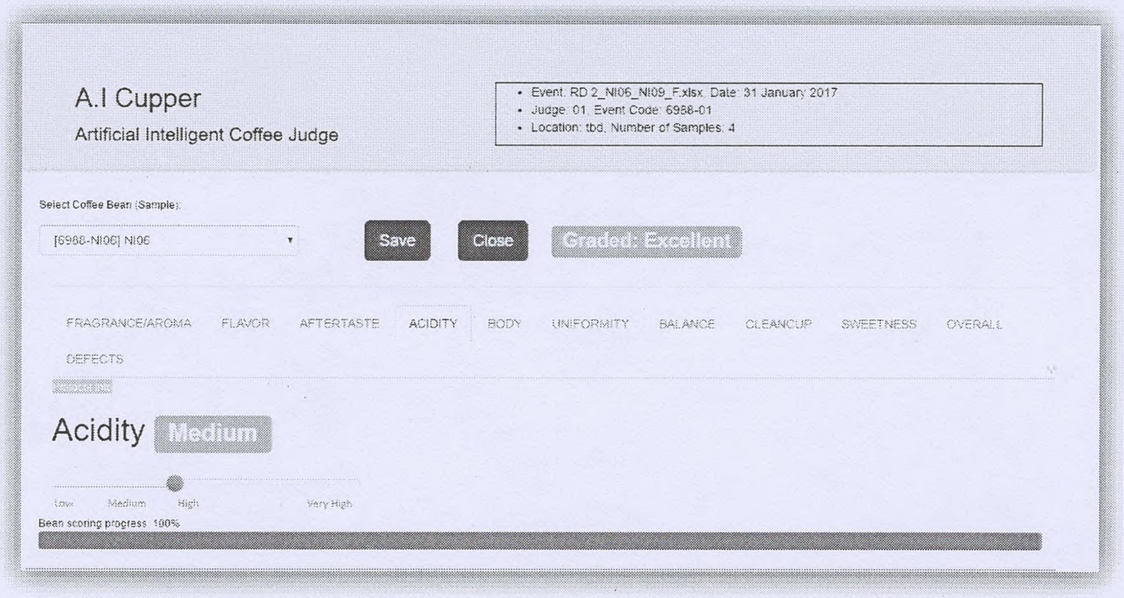


Figure 1.4.2: Actual Screen of the AI Cupper for the Acidity attribute

The Fuzzy-Based expert system's reasoning layer receives the translated scores from the UI and process them with its inference or reasoning engine. This layer is where all the fuzzy sets encompassing all the linguistic variables and all the knowledge of the coffee experts expressed in fuzzy rules come together as the fuel of the reasoning engine. The AI Cupper' Mamdani Inference Engine will process all the input coffee bean attributes and will output the coffee quality grading scores. The expert system manages the intricacy of translating the judge's perception of the coffee bean attributes into numeric values as they are expressed linguistically through the AI Cupper user interface.

Furthermore, AI Cupper could provide expertise needed for training and development in order to share the wisdom of coffee experts with a large number of other potential judges or cuppers in training. The system is able to capture and preserve the irreplaceable human expertise of the coffee judges and will capitalize on it, even providing this expertise at a number of remote locations at the same time. Eventually, once the expert system becomes part of the coffee attributes' evaluation, it could alleviate the sensorial stress to which the judge gets expose while sensing and perceiving both,

flavors and aromas to ascertain with numbers of the coffee's quality. In other words, as the cuppers perform their sensorial evaluations the previously represented knowledge will work on their behalf.

Using AI Cupper, the SCAA could capitalize on a steady, unemotional expert system capable of assisting the coffee experts in the demanding task of evaluating coffee bean attributes when grading specialty coffees with complete responses at all times. One of the major benefits of the expert system is the ability to transfer expertise from an expert to a computer system and then on to other humans (even non-experts).

1.5 Challenges

Specialty coffees are coffees of high quality. The evaluation of their attributes to measure their degree of quality has been a topic of high priority for organizations like the SCAA and its European equivalent (SCAE). In an effort to continue their impact in this global market concerning specialty coffees, the SCAA and the SCAE have agreed to unify their work. Both organizations have called out a vote of unification. The fundamental premise is that specialty coffee beans would always be well prepared, freshly roasted, and properly brewed "The Specialty Coffee Association of America (SCAA) continues to define specialty in this context."

Coffee, most often arrives in the final consumers hand after a long series of baton hand offs from farmer to miller to intermediaries to roaster to brewer, and the final experience is dependent on no single actor in the chain dropping the baton. Thus, in order to truly look at what specialty coffee is, we must examine the roles that each plays and create a definition for specialty at each stage of the game (Rhinehart, 2016). The cupping of the specialty coffees could be seeing as one of the most important step on ascertaining their quality. Nevertheless, it is known that a chain is as strong as its weakest link, the sensorial evaluation of the coffee bean attributes to determine is quality grading carries Vagueness. The SCAA cupping process is based upon a discursive model in which coffee's quality measurements are influenced by discussion, collaboration and other group dynamics. Given the significant costs and

capital outlays of the coffee industry, and related industries, deficiencies in the measurement and assessment processes can potentially result in inefficient business practices and significant market distortions with demonstrable direct and indirect business impacts.

When cupping, the expert judge writes down the individual components' scores and ranks their intensities for reference. Despite the fact the cuppers are using natural language statements in their judgment, they are required to use numerical values to evaluate the coffee bean attributes. With an expert system that uses artificial intelligence techniques such as fuzzy logic the judge's perception could be better assisted with a collection of linguistically expressed terms instead of numbers (complementary terms acting as shapers of the coffee bean's attribute score's gradation of meaning).

This research has focused in facilitating the SCAA coffee assessment process by allowing the cuppers to express with linguistic terms their perceptions of the coffee-bean attributes, as a result an expert fuzzy system, the AI Cupper was designed and developed to handle the vagueness of the process.

The adoption of usage of the AI Cupper challenges the current SCAA protocol to incorporate a tool that uses the experience of their highly trained coffee judges. One of the challenges is to re-train their coffee judges not to express their perceptions with numbers but to delegate this task to an expert system. The cupper could express linguistically their coffee bean attributes scores through the AI Cupper' user interface, see Figure 1.4.1 and 1.4.2.

1.6 Thesis Organization

This research presents a way of handling the fuzziness of the terms included in the cupping process of coffee beans, the use of Fuzzy Logic. As Professor Michael Negnevitsky remarked, "Fuzzy logic is not logic that is fuzzy, but logic that is used to describe fuzziness" (Negnevitsky, 2011, p. 87). Fuzzy logic brings a feasible possibility; it could assist interpreting the meaning of fuzzy linguistic terms/variables because it allows us to work with either a partially true or a partially false statement. In the fuzzy logic realm these variables can have different values such as low, medium and high and could

be computed, using fuzzy rules, "simulating in a certain way the human reasoning processes" (Caversan, 2009).

Chapter two incorporates some background supporting this research, and in particular due to the nature of coffee, it summarizes related work on expert systems used in agriculture products. Moreover, chapter two briefly covered traditional rule based expert systems and emphasized why we have chosen fuzzy set theory for this thesis. Chapter three encompasses the details of the proposed application the design and the developed Restful API, completely decoupled from the user interface and the data repository. This API handles HTTP requests in the form of GETS, POSTS, PUTS, and DELETES responding using standard HTTP as well sending data in JSON (Java Script Object Notation) format when requested, Figure 5.1.1.

In chapter four the Development of AI Cupper is discussed remarking its technological core and its user interface mainly based on sliders instead of dropdowns or textboxes. Chapter five presents the system evaluation. This chapter offers the details of this research in terms of the data used during the knowledge discovery (building the rules to train the system), and the preparation and inputting of the data used to test the system. Nevertheless, it is included a brief summary of the results gained during testing. It also includes the details of the SCAA standard protocol for sample evaluation and described how the AI Cupper Membership Functions were designed for each of the coffee bean attributes (input) and for the resulting coffee quality grading (output).

Chapter six contains a discussion and comparison of the results, it concludes the document and considers future work, including additional applications and some basis for further research.

Chapter 2. Background

2.1 Introduction

High quality coffees, coffees of superior aroma and flavor have sparked a considerable stream of business around the globe. These coffees are categorized as “Specialty Coffees”: coffees made from the highest quality beans (Donnet, Weatherspoon, & Hoehn, 2007). The quality of these coffees is measured by their very nature as they are judged upon a set of attributes (Fragrance/Aroma, Flavor, Acidity, etc.) which are sensorially evaluated by coffee experts (cuppers in the coffee industry).

The process of sensorial evaluation of the coffee bean attributes by cuppers, ultimately reflects the cupper’s perception of the coffee bean quality. To support the manual process of evaluating the coffee bean attributes, notes taking and score gathering, judges are trained to fill forms like the *Cupping Form* created by the Specialty Coffee Association of America (SCAA) (SCAA, 2013, p. 4) as part of their standard protocol, see Appendix C.

Since the decade of the seventies a set of computer systems that emulated the decision-making ability of human experts or Expert Systems (George J. Klir, 1995, pp. 418-441) have been a subject of study in the field of Artificial Intelligent (AI). In particular fuzzy expert systems “model the world in terms of the semantics associated with the underlying variables, thus providing a much closer relationship between real world phenomena and computer models” (Cox, 1999).

Expert systems are widely used in different domains like medical, automotive, financials and lately in agriculture. For example in 1970 the first medical expert system (MYCIN) was developed by Edward H. Shortliffe at Stanford University to help doctors prescribe medicine for blood infections. More, corresponding with the mass production and wider use of automobiles and the incorporation of complex electronic technologies, an expert system for engine fault diagnosis was proposed (Hirpa L.

Gelgele, 1998). In the financial arena an expert system for financial ration analysis was introduced for the prediction of future condition of a company's wealth based on its previous financial statements (Moynihan, Jain, McLeod, & Fonseca, 2006). Furthermore, a couple of researchers remarked that "All commercial crop production systems in existence today (1985) are potential candidates for Expert Systems" (McKinion & Lemmon, 1985).

In the following sections, the notion of expert systems, inference engines, forward and backward chaining in addition to fuzzy logic and Mamdani-style reasoning will be explained.

2.2 Rule-based Expert-systems

An expert in certain domain, "is someone with a profound knowledge along with strong practical experience in such a domain capable of expressing knowledge in form of rules for problem solving" (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011, p. 25). The foundation of what is a "rule-based expert system" was established by Newel and Simon from Carnegie-Mellon University at the beginning of the 1970s. Their model was based on how human solve problems by utilizing acquired knowledge and expressing it as production rules, just like is showing in Figure 2.2.1. The production rules are stored in the long-term memory and the problem-specific information or facts in the short-term memory.

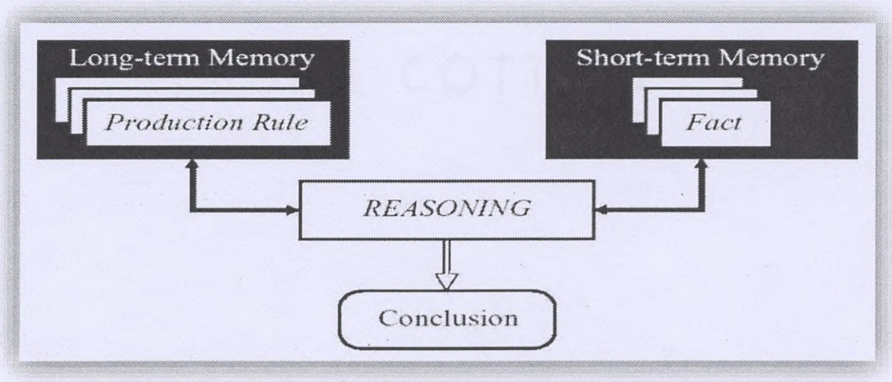


Figure 2.2.1: Adopted from (Newel and Simon, 1975[i])

In Artificial Intelligence, the most commonly used form to represent knowledge are rules. Rules are structures composed of IF-THEN parts where any given fact or information in the IF (antecedent) part implies some action in the THEN (consequent) part. Hence, a rule is capable of providing some details of how to solve a given problem, "each rule is an independent piece of knowledge" (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011, p. 50).

The knowledge represented in the set of rules of an expert system is relatively easy to create and understand. Nevertheless, a rule could be composed of several antecedents either one joined by a conjunction (AND) or a disjunction (OR) or a combination of both. The antecedent of a rule incorporates two parts: an object (linguistic object) and its value. The object and its value are linked by an operator in charge of identifying the object to assign the value.

Mathematical operators like for example less or greater than could be used to define an object as numerical and assign it to the numerical value for example: IF "age of a customer" < 18 AND "cash withdrawal" > 1000 THEN "signature of the parent" is required, Table 2.2.1

Table 2.2.1: List of Items Which Could be represented by IF-THEN rules

Item	Rule
Relation	IF the "fuel tank" is empty THEN the car is dead
Recommendation	IF the season is autumn AND the sky is cloudy AND the forecast is drizzle THEN the advice is "take an umbrella"
Directive	IF the car is dead AND the "fuel tank" is empty THEN the action is "refuel the car"
Strategy	IF the car is dead THEN the action is "check the fuel tank"; step1 complete IF step1 is complete AND the "fuel tank" is full THEN the action is "check the battery"; step2 is complete
Heuristic	IF the spill is liquid AND the "spill pH" < 6 AND the "spill smell" is vinegar THEN the "spill material" is "acetic acid"

2.2.1 Inference Engines

In the context of traditional rule-based systems when the antecedent of a rule is true then the consequent of it is true as well. The inference engine is in charge of comparing each of the rules from the knowledge repository with facts also stored in the database. As rules' precedents are matched with a given fact, the inference engines engages in "Inference Chains" (sequential rule execution) with the premise of having to decide when the rule is ought to be fired (Negnevitsky, Artificial Intelligence a Guide to Intelligent Systems - Thrid Edition, 2011, pp. 35-37)

2.2.2 Forward chaining

This is one of the most common ways of executing rules driven by data to gather information and infer upon it. The engine starts with what it is known, it moves forward with that data firing the topmost rule in a cycle known as "match-fire". Matching rules are only executed once but they could add new facts into the database (these facts are available for other rules not yet executed). These matching-firing cycles stop when no other rules are available for firing (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011, pp. 35-37).

2.2.3 Backward Chaining

This is the goal-driven inferencing process. The reasoning (inference) engine starts up with a "hypothetical solution", a goal. The inference engine search the data for evidence that could prove the hypothesis. Each of the rules' consequent (THEN) part are searched for the goal, if found and its precedent (IF) part matches data in the database the rule is fired as a way of proving the goal. Further, as the engine put aside those un- matching rules, process known as "stacking rules", it sets up a new goal (a sub-goal) trying to prove the IF part of the rule being stacked and then a search starts again

trying to prove this new goal. This process will cycle until no rules are found to prove the sub-goal (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011, pp. 38-39)

2.3 Fuzzy Logic

Fuzzy Logic is the theory of fuzzy sets, sets that calibrate vagueness. It is based on a multi-value logic or fuzzy propositions instead of a dual-value logic or classical propositions such as the Boolean logic which stems manages only two possible values, true or false. The key difference between dual-logic values and their counterpart, the multi-logic values is the range of their truth values (George J. Klir, 1995, p. 220).

In a multi-value logic there is room to handle vagueness, while a dual-value logic precision could be seem as rigidness (imposes a sharp boundary) toward our natural world which offers more than black and white perspectives of its phenomenal; a multi-value logic graciously offers the possibility of something being partially true or false under a specific context.

Fuzzy Logic is not confined with a black and white only perspective, it has a middle ground in between these two colors: a gray gradient which manages the transition from white to black and vises versa. In 1965 Professor Lofti Zadeh led the effort of maturing Fuzzy Set theory by introducing the fundamental theoretical background for applying “natural language terms: Fuzzy Logic or Fuzziness”. “Fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degree of membership rather than on crisp membership of classical binary logic” (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011, p. 89)

Fuzziness has been successfully used to measure how well an instance (value) conforms to a semantic ideal or concept and this compensates well with the imprecision of the sensorial nature of the cupping process which will be the core of the proposed AI Cupper (See Figure 2.4.1) (Cox, 1999, p. 64).

Fuzzy logic allows us to work with either a partially true or a partially false statement and favors the construction of fuzzy-based expert systems which are considered "universal aproximators" as their membership functions get approximated to pretty much any "degree of accuracy". This adjustment of the accuracy could be achieved by adjusting the rules and the granularity level in the fuzzy descriptors (Cox, 1999, pp. 18-19).

Fuzzy-based expert systems are fairly tolerant of estimations in the fuzzy set morphology and, even to the point that fuzzy sets overlap. In addition, fuzzy set shapes are prompt to quick refinement allowing the modeling process of getting the prototype in alignment with the real system with little or no hassle. Moreover, researchers have found that in the process of Fuzzy set discovery (the process of identifying and defining fuzzy sets), the knowledge acquisition process becomes easier compared with traditional rule-based expert systems (Cox, 1999, p. 12)

2.3.1 Fuzzy Rules

A fuzzy model consists of a group of conditional and unconditional fuzzy propositions or rules. These propositions are statements used to establish a relationship between a value in the underlying domain and a fuzzy space (represented by a linguistic variable) (Cox, 1999). Conditional fuzzy propositions are those qualified by an *IF* statement (similar to conventional expert system rules), it has the form "if w is Z then x is Y" where *w* and *x* are model scalar values, and *Z* and *Y* are linguistic variables. This proposition expresses that "*x* is *Y*" is conditional on the truth of the predicate, it could be interpreted as "*x* is member of *Y* to the degree that *w* is a member of *Z*" (Cox, 1999, p. 274).

Unconditional fuzzy proposition are not qualified by an *IF* statement. This propositions have the general form "*x* is *Y*" where *x* is a scalar from the domain, and *Y* is a linguistic variable. These propositions are always applied within the model serving either to restrict the output space (to the maximum truth of their intersection) or to define a default solution space. When a fuzzy model includes

both conditional and unconditional propositions, if none of the conditional rules executes, the inference engine takes the value from the space bounded by the unconditional propositions. This is the reason why unconditional fuzzy propositions must be executed before the conditional propositions (Cox, 1999, p. 275).

2.3.2 Membership Functions

In dual-logic a crisp relation flatly represents either the presence or absence of a given association, interaction or interconnectedness between the elements of two or more sets. Fuzzy logic or multi-value logic generalizes the concept of absolute presence or absence allowing various degrees of strengths of association or interaction between elements. Degrees of association can be represented by membership grades in a fuzzy relation in the same way as degrees of set membership are represented in a fuzzy set (George J. Klir, 1995).

In fuzzy logic, a membership function is a curve that represents the features of a fuzzy set by assigning to each element of the set its associated membership value (degree of membership), for example given the fuzzy set *A* its membership function $\mu_A(x)$ could be explained as follows:

$\mu_A(x): X \rightarrow [0, 1]$ where $\mu_A(x) = 1$ if x is totally in "A"

$\mu_A(x) = 0$ if x is not in "A"

$0 < \mu_A(x) < 1$ if x is partially in "A"

2.3.3 Fuzzy Reasoning

Fuzzy Expert systems reason by processing all the fuzzy statements of knowledge (fuzzy propositions) in parallel. The fuzzy inference engine evaluates each of the available fuzzy propositions and finds its degree of truth (the extent to which a preposition is true) collecting only those with some

truth making them contributors of the solution variable set (Cox, 1999, pp. 270-271). The functional relationship among the degrees of truth in related fuzzy regions is known as "the method of implication" and the relationship between fuzzy regions and the expected value of a set point is called "method of defuzzification". These two methods are the core of fuzzy reasoning also known as "approximate reasoning" (Cox, 1999, p. 271).

Whereas a fuzzy inference engine produces a fuzzy set out of the execution of each of the fuzzy propositions or rules, the fuzzy expert system is expected to produce a single number representing the expert system output. To generate a single number output, the expert fuzzy system first aggregates all output fuzzy sets obtained from each of the fuzzy rules into a single fuzzy set. This aggregated fuzzy set is defuzzified into the expected single number output. (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011, pp. 106-107)

2.3.3.1 Mamdani-style Inference

In this work we will be using Mamdani-style inference for our fuzzy inference engine. The Mamdani-style fuzzy inference technique is performed in four steps: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs and defuzzification. Fuzzification takes the input numerical values and finds out the degree to which they associate to the corresponding fuzzy sets.

Rule Evaluation is the second step of the Mamdani-style inference. The input for this step are the fuzzified values from step one. This step applies these fuzzified values to the antecedents of the fuzzy propositions. When a fuzzy proposition has more than one antecedent the fuzzy operators AND or OR are used to obtain a single result (the truth value) of the antecedent evaluation. Then this truth value is applied to the consequent membership function "the consequent membership function is clipped or scaled to the level of the truth value of the rule antecedent" (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011). Studies have shown that different methods of the fuzzy operations

produce different results (Cox, 1999) this is why some tools (fuzzy controller packages like MatLab) allow the customization of the AND and OR fuzzy operations forcing the user to make the choice (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011).

Step three of the Mamdani-style inference is the Aggregation of the rule outputs. During this step the fuzzy engine takes the membership functions of all rule consequent previously processed to produce a single fuzzy set for each of the expect output variable. The fourth and final step in the Mamdani-style fuzzy inference process is defuzzification. This step takes the aggregate fuzzy set from step three and produces an output of a single number. The Mamdani-style inference engine uses one of the most popular methods for defuzzification, the centroid technique. Its role is to find the point where a vertical line would slice the aggregate set into two equal masses process known as the center of gravity (COG).

Theoretically this center of gravity is calculated over a continuum of points in the aggregate output membership function (Negnevitsky, Artificial Intelligence, A Guide To Intelligent Systems, 2011). Nevertheless, the Mamdani-style inference engine makes its calculations based on a sample of points. This is a reasonable estimate based on the following formula:

Equation 2.3.3.1: Formula used by Mamdani-style Inference Engine to Calculate the Center of Gravity

$$COG = \frac{\sum_{x=a}^{b} \mu_A\ (\mathrm{X})\, x}{\sum_{x=a}^{b} \mu_A\ (\mathrm{X})}$$

The above formula is used to calculate the center of gravity of the fuzzy set, *A*, on the interval, [a, b]. Where $\mu_A(x)$ is the membership function of the *A* set.

2.4 Related Work

At the time of writing the thesis proposal (June 2016), by the best of our knowledge, no research work was found related to associating Fuzzy Set Theory with the Sensorial Evaluation of Coffees. Nevertheless, while finishing writing this thesis a work was published as described in this section. Flores and Pineda (2016) published a paper covering the Honduran coffee's characteristics (visual, olfactory, taste and tactile characteristics) as the Honduran Coffee Institute (IHCAFE) requires for training cuppers.

Similar to AI Cupper, Flores and Pineda's system uses a set of fuzzy rules to model the coffee quality from the input coffee attributes, however AI Cupper has the capacity of adding new fuzzy rules to its rules set (this because it includes its own Lexer to parse rules and validate them against the database). No much details was provided on the inference engine used (it seems to be Mamdani-style). To facilitate the interaction between the user and the expert system Flores and Pineda used drop-downs, one dropdown list for each of the four group of characteristics. For further flexibility, AI Cupper uses one slider per attribute that spans over four possible options "Low, Medium, High and Very High". It would have been good if the paper provided the application's architecture and what technology was used.

Flores and Garcia System like the AI Cupper was able of successfully inferred coffees bean quality with an accuracy of more than ninety five percent. More, they noticed a lot of more uncertainty toward the middle of the membership function with and error of three percent, in our case we noticed uncertainty toward both extremes the lowest and the highest quality scores with and error less than five percent (see Figures 5.1.1, 5.1.2 and 5.1.3).

As mentioned earlier, no other related work was found so an expanded literature review was done to cover fuzzy expert systems used in agriculture products in general. A summary about those systems is provided in Table 2.4.1.

Table 2.4.1: Related work on Expert Systems Used in Agriculture Products

Authors	Methods Used	Research Goals	Results
(A. Tagarakis S. Koundouras. E. I. Papageorgiou. Z. Dikopoulou S. Fountas. T. A. Gemtos 2014)	Fuzzy Inference System (FIS)	Model grape quality in vineyards based on expert knowledge (viticulture expert) for three years: 2010, 2011 and 2012	The overall agreement between FIS results and expert evaluation was 77.20 % for 2010, 81.83 % for 2011 and 82.35 % for 2012
(Shahid Bahonar 2012)	Rule-based fuzzy inference system applying the Mamdani-style fuzzy inference (MFIS)	Model Date grading evaluation and classification	For the different date varieties there was 86% general agreement between the MFIS results and the human expert
(Eduardo Llobet, J.W. Gardner, Toby Trevor Fury Mottram, 1999)	Supervised pattern recognition method based on fuzzy adaptive resonance theory (ART): The Fuzzy ARTMAP	The application of Fuzzy ARTMAP to smell discrimination (coffee, alcohol and cow's breath) with electronic nose (EN) instruments, compared with a back-propagation trained multilayer perceptron (MLP)	Using MLP: 100% alcohol, 81% for coffees and 68% cow's breath. The accuracy of the ARTMAP method was 100% with alcohol, 97% with coffee and 79% for cow's breath respectively.

(Hamid Tavakolipour, Mohsen Mokhtarian, Ahmad Kalbasi-Ashtari 2014)	A Fuzzy Expert Engine based on Mamdani-style inference and an Artificial Neural Network (ANN) to predict drying temperature	Monitoring of Zucchini moisture ratio (MR)	The ANN was able to predict MR of dried zucchini with a coefficient of determination $R^2 =$ 0.998. The fuzzy model was able to predict MR of dried zucchini with R^2, root mean square (RMSE) and a mean relative percent error (P) equal 0.919, 0.0662 and 4.416, respectively.
(Marcos Evandro Cintra, María-Carolina Monard, Heloisa De Arruda Camargo, Luis Henrique Antunes Ridrigues, 2011)	Comparing a Fuzzy based expert system using decision trees (FUZZYDT) with a classical decision tree method (J48, an implementation of C4.5)	Generation of coffee rust disease warning in Brazilian crops	FUZZYDT presented competitive error rates and models like error 15.29, standard deviation (SD) 9.56 while J48 had: error 18.72 and SD 8.59

This research work aims to design and implement a fuzzy system, *AI Cupper* that uses Mamdani-style inference engine to support the cuppers (coffee judges) in using natural language to evaluate the different features of coffee beans (like the fragrance/aroma, acidity, and so forth) rather than recording numerical scores using the Specialty Coffee Association of America (SCAA) cupping form. AI Cupper should not be able only to support cuppers but also learn from them.

Chapter 3. AI Cupper High Level Architectural Design

3.1 Introduction

This thesis aims to design and develop AI Cupper, a fuzzy expert system that would allow the cuppers to use natural language to evaluate the different features of coffee beans (like the fragrance/aroma, acidity, and so forth) rather than inputting numerical values. This chapter focuses on the high level architectural design for AI Cupper. The development of AI Cupper will be explained in detail in the next chapter.

3.2 Design Goals

AI Cupper will have an API based on Restful based web service, a light weight, highly scalable and maintainable structure to support the user interface application, a responsive client web based mobile app to be used by the judges for data input (cupping event results). The Restful service sits on top of a relational database also hosted in the cloud, Microsoft (MS) SQL Server version 2014. In addition, the Restful service is completed decoupled from the database repository and allows only Restful calls through standard HTTP requests (commands) like HTTP Get, Post, Put, Delete and Patch.

HTTP commands are the only way the database can interact with the Restful service. This Restful service is a Web.Api application using MS .Net 4.6 MVC (Model View Controller) and MS Entity Framework version 6.0 Technologies. Moreover, the Restful API should not expose database objects (Models) it must only expose the portion of the data needed (views) through each of the HTTP Get requests.

3.3 Design Challenges

Decoupling of the Restful Web.Api Service allows the exposure of the domain models (resources listed in Appendix A) through idempotence uniform resource locators (URLs). This implies that the client can make the same request again if it does not receive a response from the Restful API the first time, regardless when the same request is make again, the Restful API response would be every time consistent. We are not designing clients for specific mobile technologies like Android based (Google mobile operating system) or iOS (Apple mobile operation system). This client could run on pretty much any device with Internet access.

3.4 Design Assumptions

We are assuming that the client will only handle JSON (open-standard format that uses human-readable text to transmit data objects consisting of attribute–value pairs) messages through HTTP requests and responses, see Table 3.8.1 and Figure 5.1.1.

3.5 As-Is Architecture

Today the process of judging specialty coffees is based on the Specialty Coffee Association of America (SCAA) Cupping Form derived from their Cupping Standard Protocol. The SCAA protocol instructs the cupper (judge) to rate the coffee samples using a numeric scale "The Cupping Form provides a means of recording 11 important flavor attributes for coffee: Fragrance/Aroma, Flavor, Aftertaste, Acidity, Body, Balance, Uniformity, Clean Cup, Sweetness, Defects, and Overall" (SCAA, 2013). In the current cupping process, crisp numeric values are used to represent coffee-bean's attributes perceived by the cupper; for example, Aroma equal 7.5, Acidity equal 7, and so forth. As the cupper scores the coffee attributes he fills up the coffee form, see Figure 3.5.1.

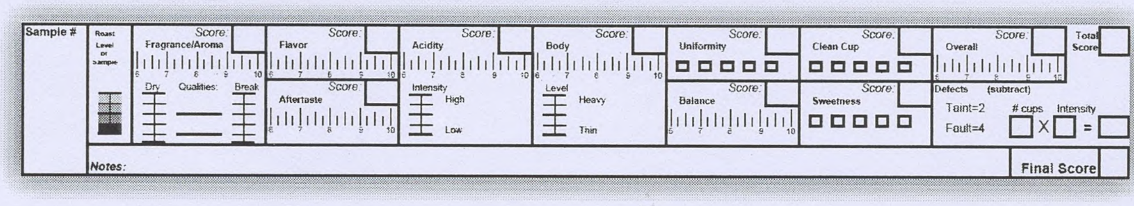


Figure 3.5.1: Strip of the SCAA Cupping Form Representing all the Attributes of a Sample (Coffee Bean)

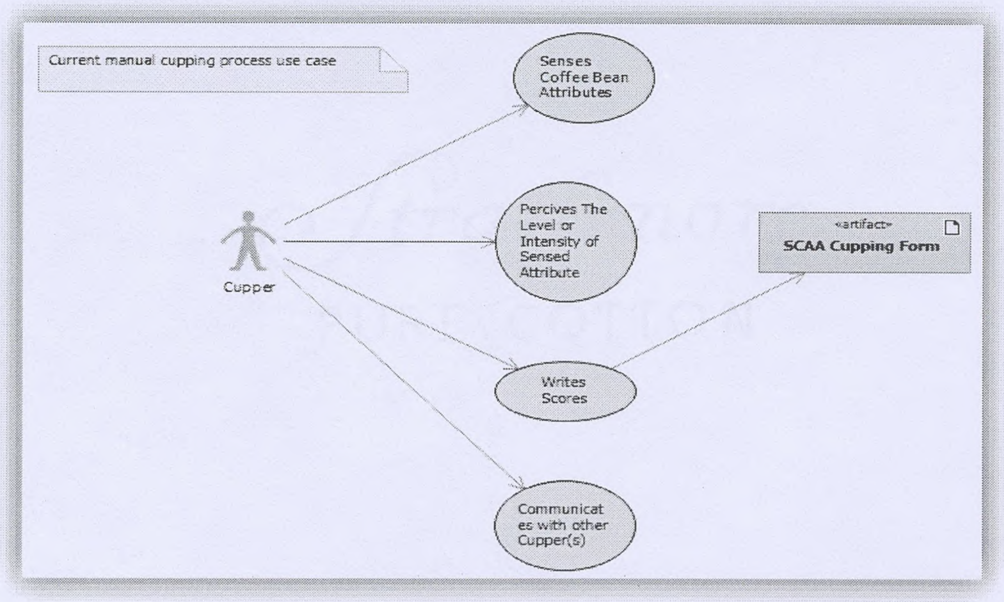


Figure 3.5.2: Current Manual Cupping Process Use Case

Figure 3.5.2 depicts current copping process as established by the SCAA cupping protocol. The cupper follows the protocol steps: first the coffee's Fragrance/Aroma is evaluated second, the Flavor, Aftertaste, Acidity, Body and Balance. Third Sweetness, Uniformity and Cleanliness including the Overall score. Finally the cupper determine the sample quality score based on all of the combined attributes. The final or total score is written in the upper right hand box of the cupping form, Figure 3.5.1.

3.6 To-Be High Level Architecture

One technique that can help with handling the fuzziness of the terms included in the cupping process of coffee beans is fuzzy logic, as Professor Michael Negnevitsky remarked, “fuzzy logic is not logic that is fuzzy, but logic that is used to describe fuzziness” (Negnevitsky, 2011, p. 87).

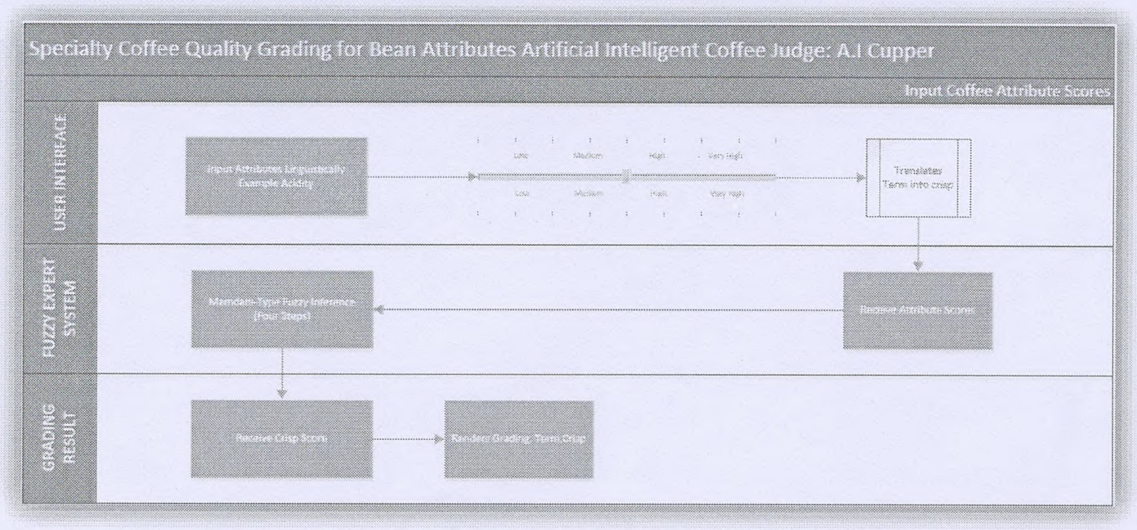


Figure 3.6.1: The Fuzzy System (AI.CUPPER) Layers

The user interface (UI) as shown in Figure 3.6.1 renders the linguistic terms associated with the coffee bean attributes (as shown for the Acidity). The interface visually renders an slider with linguistic terms representing one coffee bean attribute, it receives the judge’s selected input and translates the coffee’s attribute linguistically expressed or input scores into crisp numeric values.

The AI.CUPPER’s reasoning layer receives the translated scores from the UI and process them with its inference or reasoning engine. This layer is where all the fuzzy sets encompassing all the linguistic variables and all the knowledge of the coffee experts expressed in fuzzy rules come together as the fuel of the reasoning engine which will output the coffee quality grading scores. The reasoning layer’s main role is to receive inputs (selections from the user not numerical values) from the coffee

experts and translate them into numerical values needed as the input for the Fuzzy-Based expert system, Figure 3.6.2.

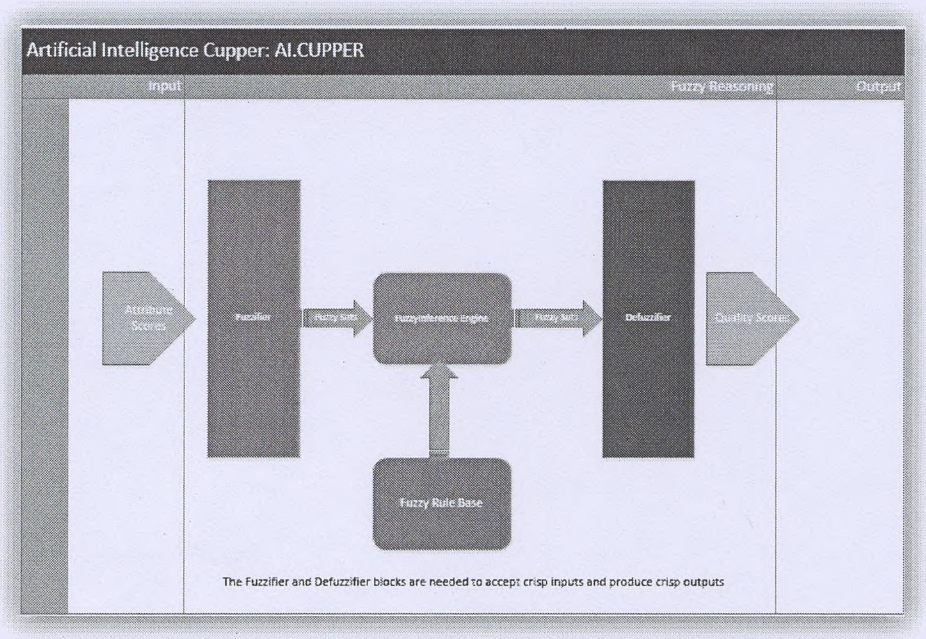


Figure 3.6.2: AI.CUPPER Mamdani-style Reasoning Engine Data Flow

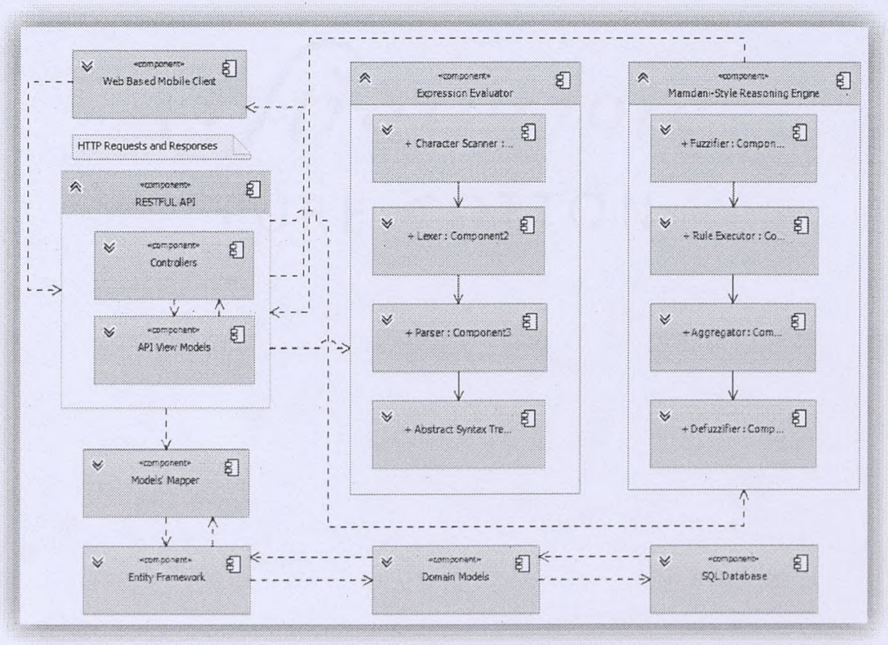


Figure 3.6.3: To-Be Detailed (Solution) Architecture Components

3.7 Summary of Expected Deliverables

Table 3.7.1 List of Deliverables

Category	Deliverable Description
Web based Mobile Client	For Cupping Results Input
RESTFUL Web.Api	Model View Controller (MVC) based Web Services to expose data and communicates with the database
Relational SQL Database	To hold cupping data and system look up and configuration data

3.8 Architectural Perspective

From this document AI.CUPPER will be developed with a core Restful API Service completely decoupling clients from the fuzzy engine and the database.

The AI.CUPPER Expert system only communicates with both, any interacting client and the service database through the Restful API. In addition, the Rest of the API internally uses the Mamdani fuzzy inference to process the coffee beans' attributes and to generate the coffee bean final grading.

Table 3.8.1: List of Detailed Perspectives

Message content	**The Restful API receives and responds with JSON string based messages. The payload of these messages max size is 262,144 bytes (256 KB)**
API Keys	The Restful API can handle key based communication (API key through HTTP request header)

Chapter 4. Development of AI Cupper

4.1 Introduction

AI Cupper offers a responsive web-based client empowered by Bootstrap (powerful mobile first front-end framework) which is fully operational and was used for testing of the Mamdani-style reasoning engine employed in this thesis. The decoupling of the Restful Web API Service only allows the exposure of the domain models (resources) through idempotence uniform resource locators (URLs). This implies that the client can make the same request again if it does not receive a response from the Restful API the first time, regardless when the same request is make again, the Restful API response would be every time consistent. The AI Cupper web based client was not designed for specific mobile technologies like Android based (Google mobile operating system) or iOS (Apple mobile operation system). This client could run on pretty much any device with Internet access, see Table 3.7.1 for detailed List of Deliverables.

4.2 Coffee Bean Attributes and Bean Grading

The coffee bean attributes were organized into two groups. One group consisting of all the attributes that are more prompt to fuzziness (seven in total. See Table 4.2.1) and a second group of four attributes consider less fuzzy or rather not fuzzy at all (four in total. Table 4.2.2).

Table 4.2.1: Group of Fuzzy Coffee Bean Attributes as described by the SCAA

Attribute	ID	Description
Fragrance	01	The aromatic aspects include Fragrance (defined as the smell of the ground coffee when still dry) and Aroma (the smell of the coffee when infused with hot water). One can evaluate this at three distinct steps in the cupping process: (1) sniffing the grounds placed into the cup

		before pouring water onto the coffee; (2) sniffing the aromas released while breaking the crust; and (3) sniffing the aromas released as the coffee steeps. Specific aromas can be noted under "qualities" and the intensity of the dry, break, and wet aroma aspects noted on the 5-point vertical scales. The score finally given should reflect the preference of all three aspects of a sample's Fragrance/Aroma.
Flavor	02	Represents the coffee's principal character, the "mid-range" notes, in between the first impressions given by the coffee's first aroma and acidity to its final aftertaste. It is a combined impression of all the gustatory (taste bud) sensations and retro-nasal aromas that go from the mouth to nose. The score given for Flavor should account for the intensity, quality and complexity of its combined taste and aroma, experienced when the coffee is slurped into the mouth vigorously so as to involve the entire palate in the evaluation.
Aftertaste	03	Defined as the length of positive flavor (taste and aroma) qualities emanating from the back of the palate and remaining after the coffee is expectorated or swallowed. If the aftertaste were short or unpleasant, a lower score would be given.
Acidity	04	Is often described as "brightness" when favorable or "sour" when unfavorable. At its best, acidity contributes to a coffee's liveliness, sweetness, and fresh- fruit character and is almost immediately experienced and evaluated when the coffee is first slurped into the mouth. Acidity that is overly intense or dominating may be unpleasant, however, and excessive acidity may not be appropriate to the flavor profile of the sample. The final score marked on the horizontal tick-mark scale should reflect the panelist's perceived quality for the Acidity relative to the expected flavor profile based on origin characteristics and/or other factors (degree of roast, intended use, etc.). Coffees expected to be high in Acidity, such as a Kenya coffee, or coffees expected to be low in Acidity, such as a Sumatra coffee, can receive equally high preference scores although their intensity rankings will be quite different.
Body	05	The quality of Body is based upon the tactile feeling of the liquid in the mouth, especially as perceived between the tongue and roof of the mouth. Most samples with heavy Body may

		also receive a high score in terms of quality due to the presence of brew colloids and sucrose. Some samples with lighter Body may also have a pleasant feeling in the mouth, however. Coffees expected to be high in Body, such as a Sumatra coffee, or coffees expected to be low in Body, such as a Mexican coffee, can receive equally high preference scores although their intensity rankings will be quite different.
Balance	07	How all the various aspects of Flavor, Aftertaste, Acidity and Body of the sample work together and complement or contrast to each other is Balance. If the sample is lacking in certain aroma or taste attributes or if some attributes are overpowering, the Balance score would be reduced.
Overall	10	The "overall" scoring aspect is meant to reflect the holistically integrated rating of the sample as perceived by the individual panelist. A sample with many highly pleasant aspects, but not quite "measuring up" would receive a lower rating. A coffee that met expectations as to its character and reflected particular origin flavor qualities would receive a high score. An exemplary example of preferred characteristics not fully reflected in the individual score of the individual attributes might receive an even higher score. This is the step where the panelists make their personal appraisal.

Table 4.2.2: Group of Not Fuzzy Coffee Bean Attributes as described by the SCAA

Attribute	ID	Description
Uniformity	06	Refers to consistency of flavor of the different cups of the sample tasted. If the cups taste different, the rating of this aspect would not be as high. 2 points are awarded for each cup displaying this attribute, with a maximum of 10 points if all 5 cups are the same.
Cleancup	08	Refers to a lack of interfering negative impressions from first ingestion to final aftertaste, a "transparency" of cup. In evaluating this attribute, notice the total flavor experience from the time of the initial ingestion to final swallowing or expectoration. Any non-coffee like

		tastes or aromas will disqualify an individual cup. 2 points are awarded for each cup displaying the attribute of Clean Cup.
Sweetness	09	Refers to a pleasing fullness of flavor as well as any obvious sweetness and its perception is the result of the presence of certain carbohydrates. The opposite of sweetness in this context is sour, astringency or "green" flavors. This quality may not be directly perceived as in sucrose-laden products such as soft drinks, but will affect other flavor attributes. 2 points are awarded for each cup displaying this attribute for a maximum score of 10 points.
Defects	11	Are negative or poor flavors that detract from the quality of the coffee. These are classified in two ways. A taint is an off-flavor that is noticeable, but not overwhelming, usually found in the aromatic aspects. A "taint" is given a "2" in intensity. A fault is an off-flavor, usually found in the taste aspects, that is either overwhelming or renders the sample unpalatable and is given an intensity rating of "4". The defect must first be classified (as a taint or a fault), then described ("sour," "rubbery," "ferment," "phenolic" for example) and the description written down. The number of cups in which the defect was found is then noted, and the intensity of the defect is recorded as either a 2 or 4. The defect score is multiplied and subtracted from the total score according to directions on the cupping form.

4.3. Building the Knowledge-base in AI Cupper

The AI Cupper does not allow the input of numeric scores for the coffee attributes listed in Tables 4.2.1 and Table 4.2.2 except for any given defects. The AI Cupper Mamdani Fuzzy Engine has seven linguistic input variables, one linguistic variable for each of the coffee attributes described in the Table 4.2.1. The knowledge required for the construction of the Fuzzy Rules was leveraged from a dataset of eighty seven coffee beans from countries including Colombia, Ethiopia, Guatemala, El Salvador, Nicaragua, Costa Rica, Mexico, Honduras, Nicaragua and Dominican Republic (Table 4.3.1

shows a portion of the data). These coffees were judged by a dozen of expert cuppers using the SCAA Cupping Form shown on Figure 4.3.1.

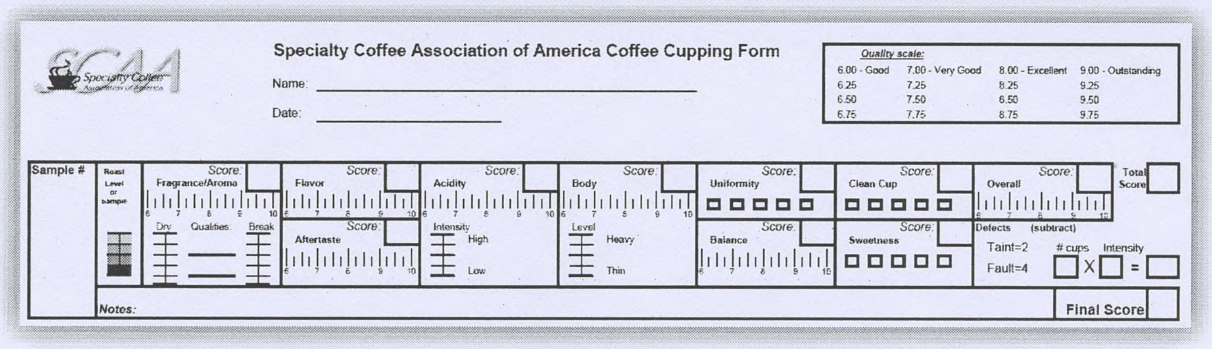


Figure 4.3.1: An Excerpt of the SCAA Cupping Form

Table 4.3.1: Portion of the available data from a total of 1056 rows

Fragrance	Flavor	Aftertaste	Acidity	Body	Uniformity	Balance	Cleancup	Sweetness	Overall	Defects
7.75	8.25	8	7.75	7.75	10	8	10	10	8	0
7.5	7.75	7.5	7.75	8	10	8	10	10	7.5	0
7.75	7.25	7	7.5	7.5	10	7.5	10	10	7	0
7.75	8.25	8.25	7.75	8	10	8	10	10	8.25	0
7.5	7.75	7.5	7.75	7.5	10	7.75	10	10	7.75	0
7.25	7.5	7.25	7.25	7.75	10	7.5	10	10	7.25	0
7.5	7.5	7.25	7.25	7.5	10	7.25	10	10	7.5	0
7.75	7	7	7.5	7.75	10	7.5	10	10	6.75	2
7.25	6.25	6	6.5	6.5	10	6.5	0	10	6	10
7.75	8.5	8.25	7.75	8.25	10	8	10	10	8.5	0

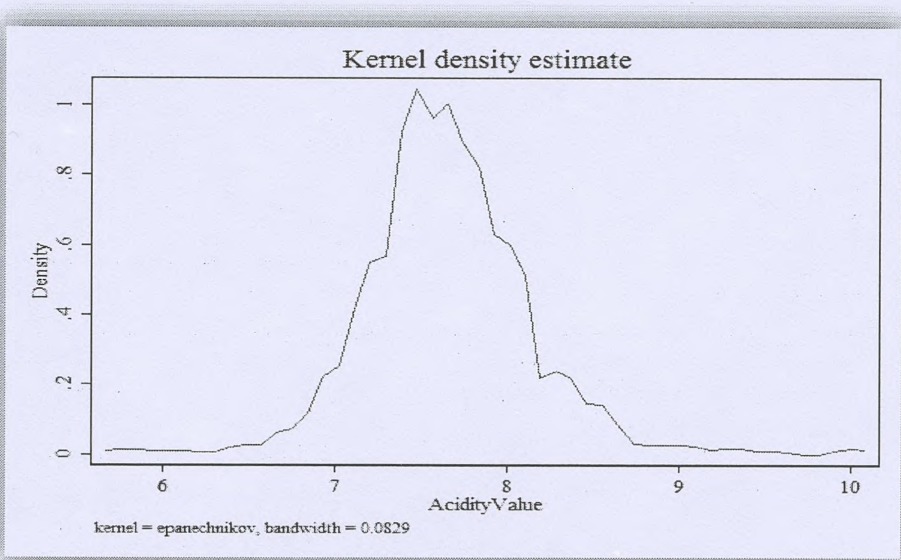


Figure 4.3.2: Kernel Density Estimate of the Attribute "Acidity"

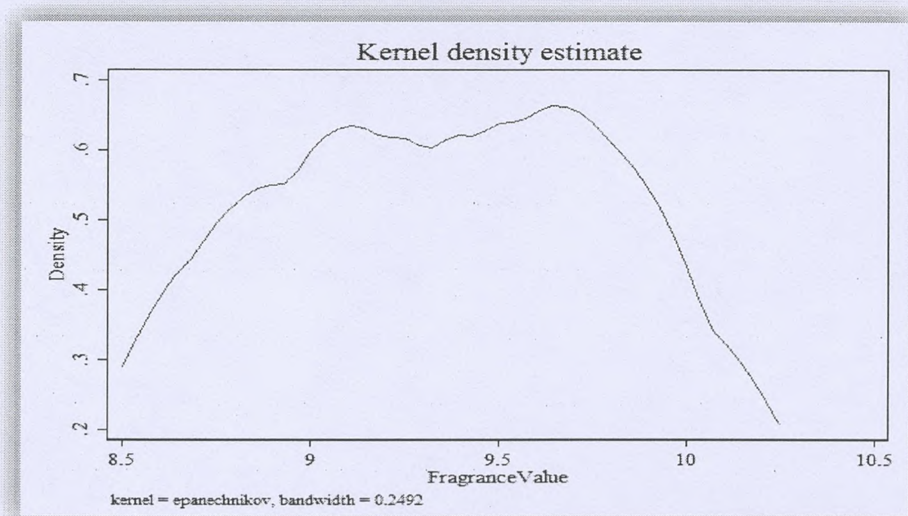


Figure 4.3.3: Kernel Density Estimate of the Attribute "Fragrance"

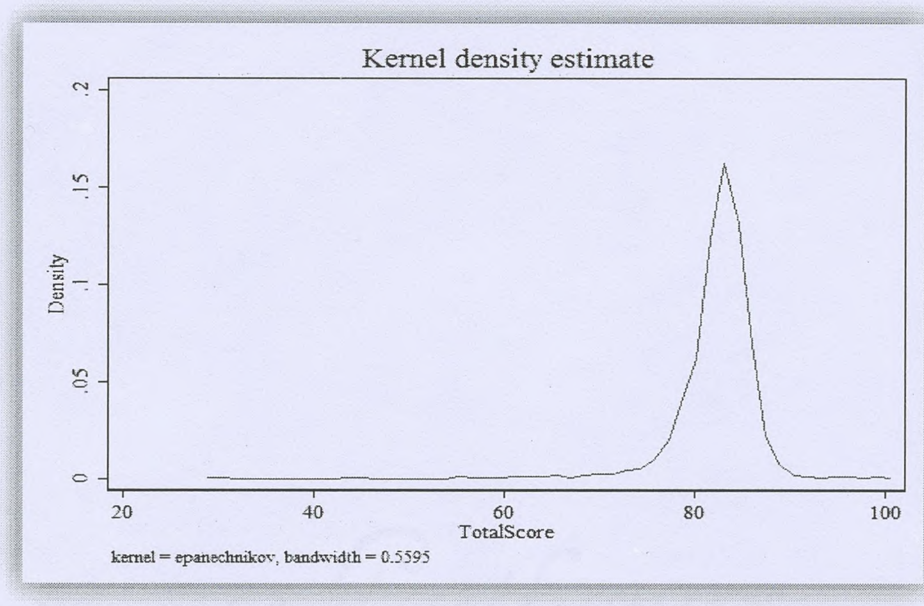


Figure 4.3.4: Kernel Density Estimate of the Total Score

By looking at the data we were able of identifying that the attributes scores were not normally distributed, see Figures 4.3.2, 4.3.3 and 4.3.4. This led us to adopt a non-parametric test for the analysis (Lazar, Heidi, & Hochheiser, 2010, p. 74) when generating the fuzzy rules (due to the fact that there is only one overlapping score value in the bin representing the intersection between the fuzzy set "low" and "medium", "medium" and "high" and one for "high" and "very high", see Table 4.3.2).

Table 4.3.2: Overlapping Score Values between Fuzzy Sets

Fuzzy sets	Overlapping score
"low" – "medium"	7
"medium" – "high"	8
"high" – "very high"	9

Instead of taking the approach of using a fitting method when evaluating the attributes' values when they overlap, we used a random number generator to empirically assign values to the overlapping

distributions. A random number between one and ten is generated, if the value is less than five we pick the term at the lower side of the fuzzy set. For example, if we are empirically generating the possibility of the term for the overlap between “low” and “medium” (seven) and the random generated number is greater than 5, we will pick “medium” otherwise “low”.

The AI Cupper application includes two modules (the AI.Cupper.DataPreparation and the AI.Cupper.ExpressionEvaluator) where the processes to generate the rules are present in a form of a libraries. These libraries’ modules were used to automatically parse and construct the rules. In addition, in order to construct the antecedent of the rules each of the attributes values were compared with the quality score shown in Table 4.3.3. In the group of the seven fuzzy attributes, each of these attributes ranges from the 6.0 to 9.75 with increments of 0.25 as shown in Table 4.3.3.

Table 4.3.3: SCAA Coffee Attributes Quality Scale

Good	Very Good	Excellent	Outstanding
6.0	7.0	8.0	9.0
6.25	7.25	8.25	9.25
6.50	7.50	8.50	9.50
6.75	7.75	8.75	9.75

The calculation of a coffee bean or sample quality grading is done by adding all the individual attributes’ scores and subtracting any found defect. This is described by the SCAA cupping standard protocol (SCAA, 2013, p. 3).

Table 4.3.4: SCAA Coffee Bean Quality Scale

Good	Very Good	Excellent	Outstanding
>= 60 < 70	>= 70 < 80	>= 80 < 90	>= 90

To construct the rules in the knowledge base, a total of the seven fuzzy attributes, shown in Table 4.2.1, are used as the antecedents and the bean quality score, shown in Table 4.3.4, is used for the consequent. Three hundred and two (302) If –Then rules were extracted from the provided data as follows (more example rules can be found in Appendix B):

"If fragrance is high and flavor is high and aftertaste is medium and acidity is high and body is medium and balance is high and overall is high Then grading is excellent"

"If fragrance is high and flavor is high and aftertaste is high and acidity is high and body is high and balance is high and overall is high Then grading is excellent"

4.4 Mamdani Trapezoidal Membership Functions

Trapezoidal membership functions are very popular (Marchant, 2007) and proved, empirically, to work well (Barua, Mudunuri, & Kosheleva, 2012).

Table 4.4.1: List of Trapezoidal Functions used in the AI Cupper for the Input Fuzzy Sets

Fuzzy Set	Trapezoidal Function Parameters
Low	6, 6, 6.75, 7.25
Medium	6.75, 7, 7.75, 8.25
High	7.75, 8, 8.75, 9.25
Very High	8.75, 9, 9.75, 9.75

Table 4.4.2: List of Trapezoidal Functions used in the AI Cupper for the Output Fuzzy Set

Fuzzy Set	Trapezoidal Function Parameters
Good	42, 42, 46, 49
Very Good	46.75, 49, 54, 56
Excellent	54.25, 56, 61, 63
Outstanding	61.25, 63, 68.25, 68.25

Trapezoidal membership functions were selected over triangular membership functions as they offered a good match of the score's values (taken from training data) when plotted within the function. Each trapezoidal membership function has four fuzzy sets; Low, Medium, High and Very High.

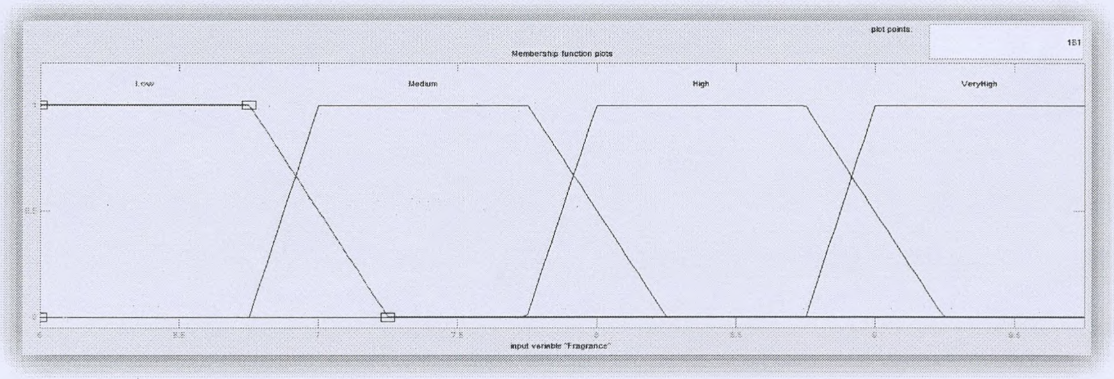


Figure 4.4.1: The Trapezoidal Membership Function for the Fragrance Fuzzy Variable

The rest of the attributes included in Table 4.2.1 share the same membership function as the one shown on Figure 4.4.1, supported by the trapezoidal functions listed in Table 4.4.1.

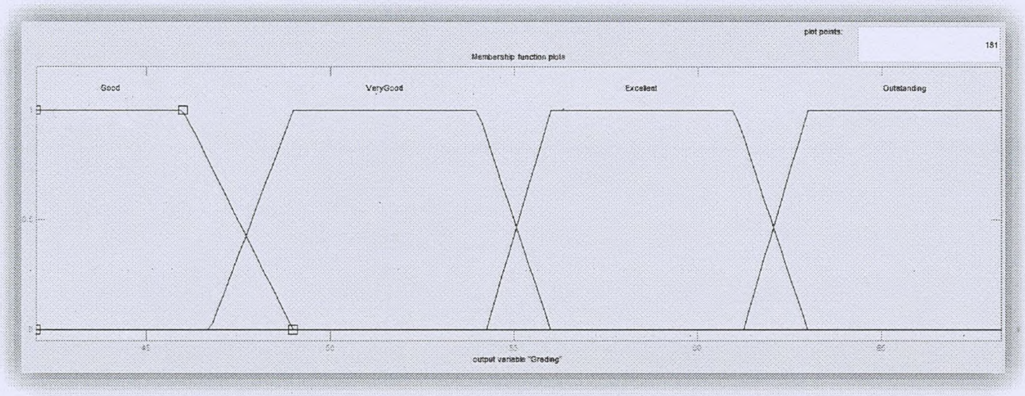


Figure 4.4.2: Fuzzy Sets representing the output variable of "Grading"

The AI Cupper outputs inferred specialty coffee quality grading scores using the grading membership function, Figure 4.4.2, supported by the trapezoidal functions listed in Table 4.4.2. The inferred grading has possible values listed in Table 4.3.4. The range of values for the grading is between 42 and 68.75 score points. This range is based in the minimum (6 * 7) and maximum (9.75 * 7) possible values any of the seven fuzzy terms could have.

4.5 Cupper User Interface (UI) Facilitates Inputting Linguistic Terms for Fuzzy Attributes

The AI Cupper takes advantage of sliders. Sliders are considered imprecise when use for selecting precise numeric values "The wider or the denser the range selectable through a slider, the harder it is to select a precise value" (Bedford, 2015).

Due to the level of imprecision involved when picking the attributes' score numerical values, the AI Cupper renders sliders for picking from a handful of linguistic terms: "Low", "Medium", "High" and "Very High". The slider approach has proven to be suitable for supporting the coffee judges to visually select the terms while describing their finding. This is due to the fact that precise values are not the core of the Fuzzy Reasoning Engine behind AI Cupper Figure 4.5.1.

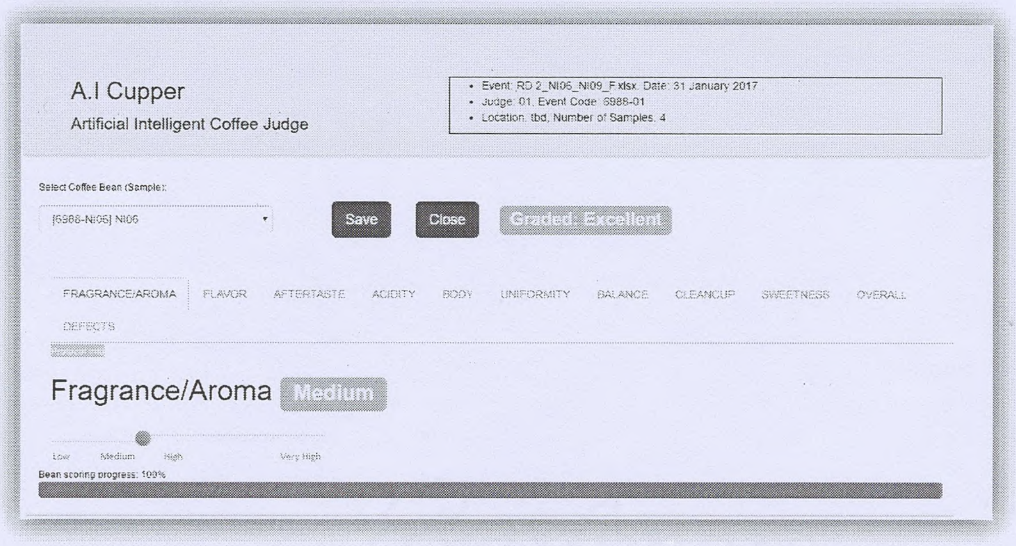


Figure 4.5.1: AI Cupper Input of Coffee Attribute Fragrance

In Figure 4.5.1 The AI Cupper shows that one of the four coffee beans has been graded as "Excellent" by the judge with the event code of "6988-01". This Figure also shows that the attribute of Fragrance has been given the term of "Medium".

Figure 4.5.2: AI Cupper Selection of Coffee Attribute Cleancup

On Figure 4.5.2 the AI Cupper shows that the Judge has given two score points to each of the five cups for the Cleancup attribute, Table 4.2.2 has this attribute description and Figure 4.5.3 its protocol's narrative as specified by the SCAA cupping protocol (SCAA, 2013).

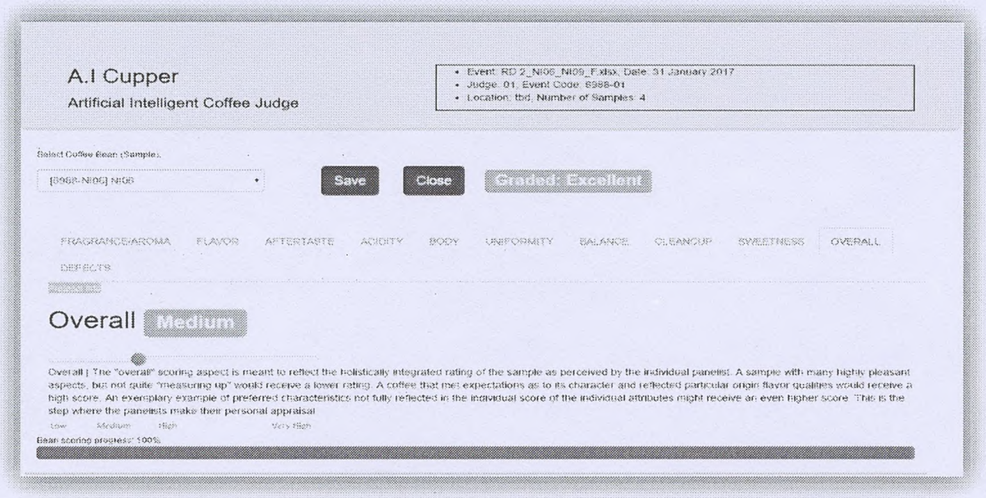


Figure 4.5.3: AI Cupper Selection of Coffee Attribute Overall and its descriptive narrative

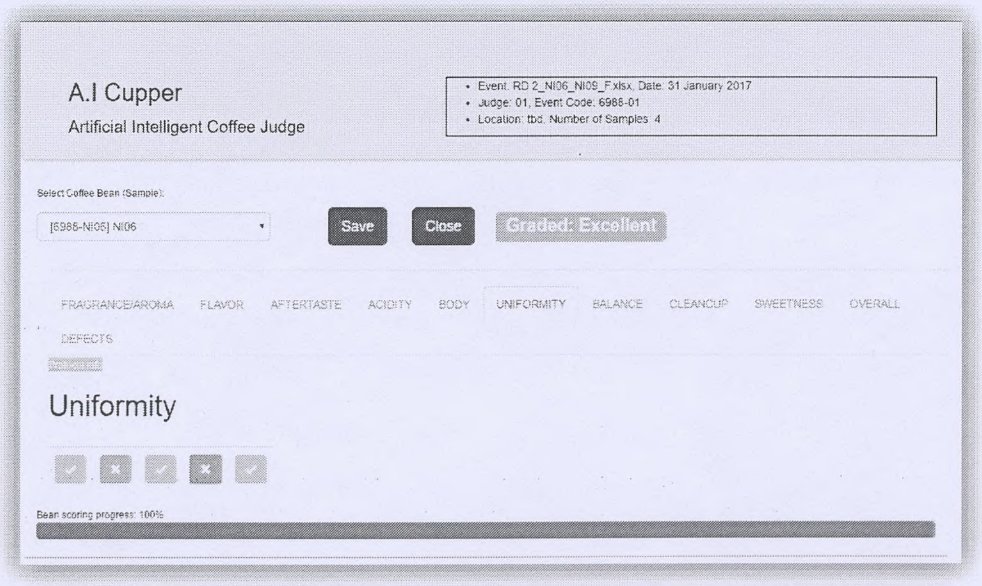


Figure 4.5.4 Uniformity, Cleancup and Sweetness are represented by Checkboxes

Each of the check boxes represents a cup of coffee used in evaluating the coffee beans. Two points are given for each checked one. The Cleancup, Uniformity and Sweetness attributes all start with ten points by default. When the judge sees that one of the cups is not in alignment with the attributes' quality they deemed it not to be awarded by un-checking it, this takes off two points from the total score, see Figure 4.5.4. When AI Cupper saves this information as part of the cupping data, these attributes take the form of "[1]-[1]-[1]-[0]-[1]" and are saved in the column titled "GivenMarkedScore" as shown in Table 5.2.2. The present of "[1]" indicates that the cupper did not un- check the corresponding cup (rendered on the screen with a light blue check mark) and "[0]" indicates that the judge ruled to discount two points from that particular cup (this is rendered on the screen as an orange squared with an x in the middle).

Chapter 5. System Evaluation

5.1 Introduction

The AI Cupper evaluating mainly focused on its Restful API performance. The same data used to test the system input through the user interface was processed using a windows console application making HTTP GET Calls onto the Restful API. Figure 5.1.1 shows how the API calls look like.

Figure 5.1.1: HTTP Request and its Response, in JSON Format, from the AI Cupper API*

The information passed into the API fuzzy engine consisted of the following cupping event key fields: first the CuppingEventID represented the unique identifier of a previously input cupping event. Second the JudgeEventCode which represents the code used to identify a particular judge during the cupping event and the CoffeeBeanSampleId holding the code used to identify a particular coffee bean during the cupping event (see Table 5.2.1).

5.2 Testing AI Cupper

The AI Cupper system was tested by inputting seventy three coffee beans judged by nine cuppers. These coffees were from several countries including Colombia, Ethiopia, Costa Rica, El Salvador, Mexico, Dominican Republic, Guatemala, Nicaragua and Honduras.

*The actual file can be accessed at: http://www.aicupper.com/api/fuzzyengine?cuppingEventid=6211&judgeEventcode=6211-08&coffeeBeanSampleId=6211-NI01

Figure 5.2.1 AI Cupper Landing Page (www.AICupper.com/UI/start.aspx)

The cupping of the seventy three coffee beans were group into fourteen cupping events as shown in Table 5.2.1. Each one of these cupping events represents a group of coffee beans and the corresponding cuppers in charge of evaluation each of the individual attributes described in Tables 4.2.1 and 4.2.2.

Table 5.2.1: List of input Cupping Events

Cupping Event ID	Cupping Event Number Of Samples	Cupping Event Number Of Judges
6988	4	9
7765	5	7
8542	5	9
9319	5	8
10096	5	9
10873	5	9

11650	5	9
12427	6	9
13204	5	9
13981	6	8
14758	4	9
15535	5	9
16312	4	8
17089	4	8

All of the fourteen cupping events shown in Table 5.2.1 were input into the AI Cupper, Figure 5.2.1 and part of the results are shown Table 5.2.2.

The AddedScore is equal to the addition of Fragrance, Flavor, Aftertaste, Acidity, Body, Balance and the Overall scores. The InputScore is equal to Uniformity + Cleancup + Sweetness – Defects. The InferredScore was inferred by the Mamdani Fuzzy Engine. The GradingTerm was determined based on AddedScore + InputScore and the InferredGradingTerm was determined based on InferredScore plus InputScore.

Table 5.2.2 Excerpt of Input and Inferred Grading Scores

InferredScore	AddedScore	GradingTerm	InferredGradingTerm	InputScore
54.93	56	Excellent	Excellent	30
54.61	52.25	VeryGood	Excellent	26
54.61	52	Excellent	Excellent	30
54.22	54.25	Excellent	Excellent	30
50.12	50	VeryGood	VeryGood	26
55.73	55.75	Excellent	Excellent	30

54.61	51	VeryGood	Excellent	26
53.61	54	Excellent	Excellent	30
55.73	56.25	Excellent	VeryGood	24
54.42	54.75	Excellent	Excellent	28

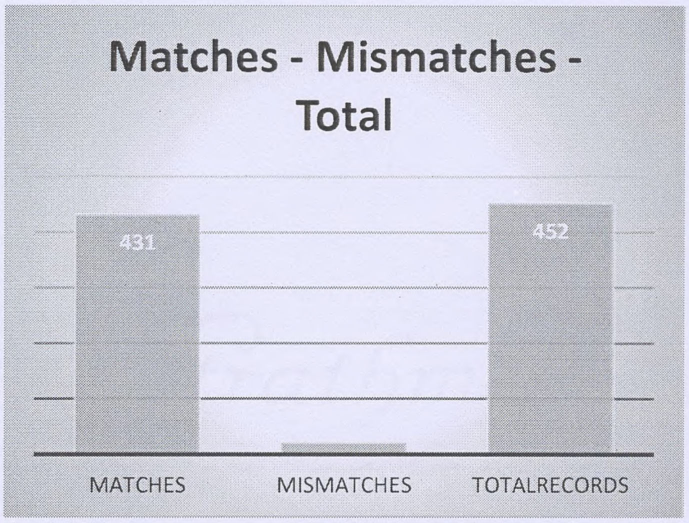


Figure 5.2.2 Grading Matches, Mismatches and Total Records

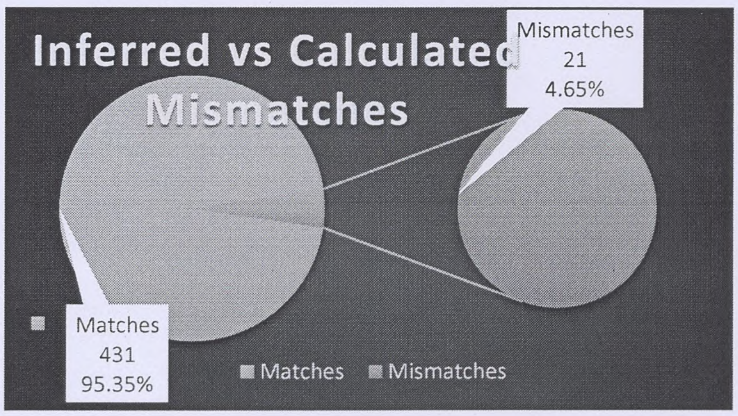


Figure 5.2.3 Grading Matches, Mismatches and Total Records expressed in percentage

The AI Cupper Mamdani-style inference engine worked over the Fuzzy Attributes listed in the Table 4.2.1. In other words out of the eleven attributes to be processed, the Fuzzy engine focused on

seven of them, the other four attributes listed in Table 4.2.2, three of them were added (resulting in the AddedScore in Table 5.2.2) and then if there was any value in the eleventh attribute (Defects) it was subtracted from this addition becoming the result of the InputScore shown in Table 5.2.1.

Figure 5.2.2 and 5.2.3 show that the AI Cupper Mamdani-style Fuzzy engine was able of matching the GradingTerm with the InferredGradingTerm in Table 5.2.2, ninety five out of each one hundred of the processed cupping events.

Chapter 6. Discussion and Conclusion

6.1 Introduction

The AI Cupper has been tested, real cupping events' data was received through its user interface. Each of the individual cupping event's representing the judge's perception of the evaluation of the individual coffee attributes was carefully input by using the application sliders to express with linguistic terms the set of fuzzy attributes' values (see Table 4.2.1).

Moreover, the set of not fuzzy attributes were input through checkboxes and few dropdowns (see Table 4.2.2), allowing the AI Cupper Mamdani-style Fuzzy Engine output coffee beans' quality grades with high accuracy (see Figures 5.2.1 and 5.2.2).

6.2 Overall Results

In this research knowledge from experts (Coffee experts relay on their expertized and knowledge when evaluating a coffee bean's attributes) has been used to design a system serving the purpose of going beyond the scope of just capturing and plotting the cupping data without any reasoning neither offering a possible alternative solution. The result of this research is the AI Cupper (Artificial Intelligent Coffee Judge) a multi-layer enterprise level application. The AI Cupper targets the protocol designed by the Specialty Coffee Association of America (SCAA) which intention is to find out if the quality claimed by the coffee sales representative matches what their judges find.

The literature review shows that although many research efforts have been done regarding the use of Fuzzy Set theory in several fields including agriculture, there is a gap in the literature where no work was found that address the use of fuzzy expert systems to evaluate coffee beans attributes. However, just recently, a paper associating fuzzy set theory with the sensorial evaluation of coffees has been published and has been considered for comparison purposes in this thesis. The paper presents the Expert Coffee Evaluation System developed by Flores and his colleague which seems to use the same

membership function used in AI Cupper that is Mamdani's fuzzy inference method. On the other side, the Expert Coffee Evaluation System's knowledge base is based on data from Honduran Coffees, accordingly the system can evaluate Honduran coffee beans only. AI Cupper is more general in that sense as its training data has coffees from several countries including Honduras so a broader knowledge base has been created. One advantage of AI Cupper over the Expert Coffee Evaluation System is its ability to learn for its users; the AI Cupper has the capacity of adding new fuzzy rules to its rules set. This because it includes its own Lexer to parse rules and validate them against the database, Figure 3.6.3. The AI Cupper API keeps in memory (caches) the list of available fuzzy rules from its repository to avoid reading them from the database each time they are needed. Nonetheless, when the Mamdani-Style Fuzzy engine engages the evaluation of these rules based on the input data (the data coming from any given cupping event) it uses its internal libraries, the DataPreparation and the ExpressionEvaluator to dynamically construct the rule. Once the rule has been constructed, the AI Cupper traverses the rule repository in memory, if the rule is not found the AI Cupper will add it into the database and refreshes the in memory repository.

AI Cupper performed pretty well with a testing data-set with a variety of coffees and judges from different countries. Using the AI Cupper user interface we were able of replicating (without inputting numeric values for the coffee attributes of Fragrance, Flavor, Acidity, Aftertaste, Body, Balance and Overall) several cupping events. Four linguistic terms were selected to replace the numerical ranges coffee judges use to grade coffee, these terms are: LOW, MEDIUM, HIGH and VERY HIGH. These four terms would be what the judges input (see Figure 4.5.1) to grade each coffee bean's attribute.

Once each attribute is graded the final grade of the coffee's quality can be either: "GOOD", "VERY GOOD", "EXCELLENT" AND "OUTSTANDING" which are the same grades the Specialty Coffee Association of America utilizes. The Mamdani-style inference engine was consistently outputting an accuracy of a little more than ninety five percent (95%, Chapter 5). On the less than five percent where

the engine failed to match the quality grading fell, we can identify both of the extremes (coffees with very low or very high grading scores) we spotted on the training data: few coffees with the specialty grading of “Good” (lowest score) and a handful of coffee samples graded as “Outstanding” (highest).

Figure 6.2.1, 6.2.2 shows the percentiles for the lowest (6.0 to 7.25) and highest ranges of the attribute scores (9.0 to 9.75). In addition Figure 6.2.3 shows a histogram of the given values for the Fragrance attribute’s scores concentrating in the ranges of 7.50 and 8.0. The rest of the attributes (including Acidity, Body, Aftertaste, etc.) showed a similar concentrations, resulting on what we observed in the total scores as shown on Figure 4.3.4.

Variable	Obs	Percentile	Centile	— Binom. Interp. — [95% Conf.	Interval]
fragrancev~e	1,056	1	6	6	6
		2	6.535	6	6.75
		3	6.75	6.689102	7
		4	7	6.75	7
		5	7	7	7
		6	7	7	7
		7	7	7	7
		8	7	7	7
		9	7	7	7
		10	7	7	7.25
		11	7	7	7.25
		12	7.25	7	7.25
		13	7.25	7	7.25
		14	7.25	7.25	7.25
		15	7.25	7.25	7.25
		16	7.25	7.25	7.25
		17	7.25	7.25	7.25
		18	7.25	7.25	7.25
		19	7.25	7.25	7.25
		20	7.25	7.25	7.25
		21	7.25	7.25	7.25
		22	7.25	7.25	7.5
		23	7.25	7.25	7.5
		24	7.25	7.25	7.5

Figure 6.2.1: Percentiles of fragrance for scores six to seven point twenty file (low scores)

90	8.25	8.25	8.25
91	8.25	8.25	8.5
92	8.25	8.25	8.5
93	8.5	8.25	8.5
94	8.5	8.5	8.5
95	8.5	8.5	8.5
96	8.5	8.5	8.75
97	8.75	8.5	9
98	9	8.75	9.25
99	9.25	9	10
100	10	10	10*

Figure 6.2.2: Percentiles of fragrance for scores eight point twenty five to nine point twenty five (high scores)

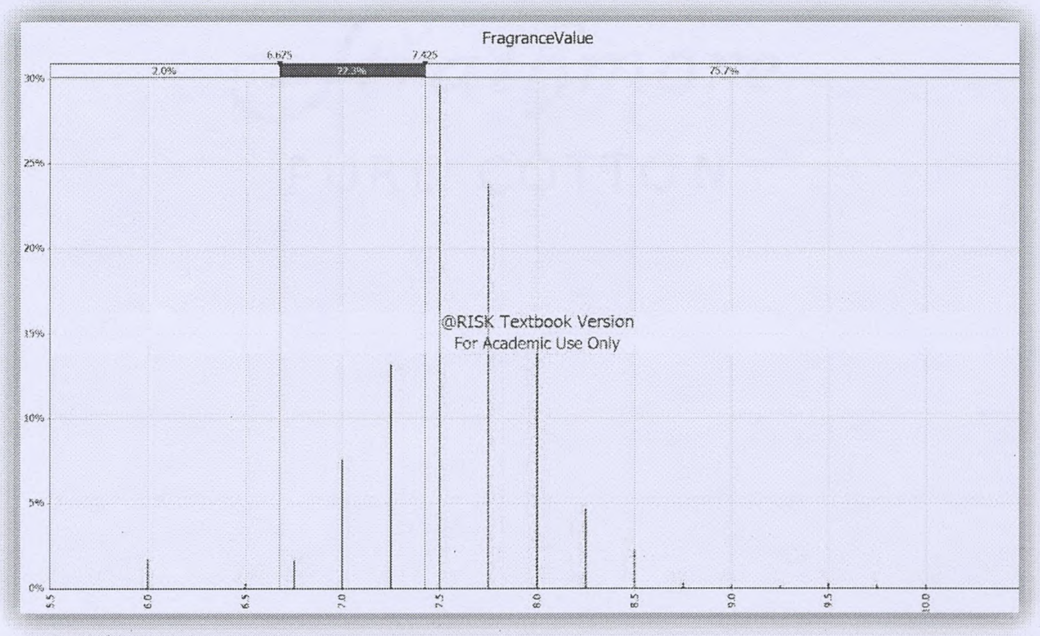


Figure 6.2.3: Histogram of Fragrance scores showing a small percentage on the lower grading which is similar at the highest scores

6.3 Validity

On this work the AI Cupper user interface have been introduced (Chapter 3 and 4). The user interface allows the coffee judge to express the coffee attributes' scores with linguistic terms instead of numeric values. Fuzzy logic dictates that for a linguistic variable to be amenable to its mathematical

framework it must have an underlying numerical quantity. This is the core of the SCAA's current coffee sensorial evaluation protocol which allows each of the coffee bean attributes to be measured with numerical values, Table 4.2.2.

The AI Cupper's user interface features sliders to allow the selection of the linguistic terms ("Scores and Grading Expressed Linguistically" Chapter 4). As the user selected linguistic terms instead of writing down numbers, the AI Cupper recorded the numeric values (given scores) associated with the selected linguistic terms, see Table 4.3.2.

6.4 Potential Error

Once we analyzed the training data and learned that needed to take a non-parametric statistical approach due to the fact that our data was not normally distributed (Chapter 4). We know that we had introduced some error when empirically selected the linguistic term for the overlapping scores found in between the linguistic terms when generating the fuzzy rules from the training data. Table 4.3.2 (Overlapping Score Values between Fuzzy Sets). Nevertheless, we used a random number generator instead of KDE (kernel density estimation) because there is only one value in each of the overlapping areas.

6.5 Conclusion

Despite the challenge introduced when expecting the coffee experts to express their finding linguistically, the AI Cupper's user interface has captured with a significantly accuracy the attributes' scores. We have gathered the grades given to several coffees by human cuppers and we had the AI Cupper to grade the same batch of coffees and found that when we compared the grades given by both the human cuppers and the AI Cupper there was a 95% matching in all the coffee quality grading, meaning that 95% of all the given grades were identical (see Figures 5.2.2 and 5.2.3).

This showed that it is possible to grade coffee utilizing only words while still following the grading standards of the Specialty Coffee Association of America. Not only is the AI cupper able to

adhere to these standards but we also believe that the AI Cupper is capable of alleviating the stress of evaluating coffee using words yet having to express these words with numbers.

6.6 Future Work and Scalability of the AI Cupper

As remarked in section 6.4 above, there is a potential error due to the use of a random number generator when automatically generating the fuzzy rules due to the overlapping in the membership functions. The use of kernel density estimation could significantly reduce this error by at least having two values in the overlapping areas, see Table 4.3.2.

The generation of the fuzzy rules based on the training data (extracting the expert knowledge) could significantly improve by limiting the range of the random number when generating the empirical values of the overlapping scores based on the training data by looking at the density of the scores values.

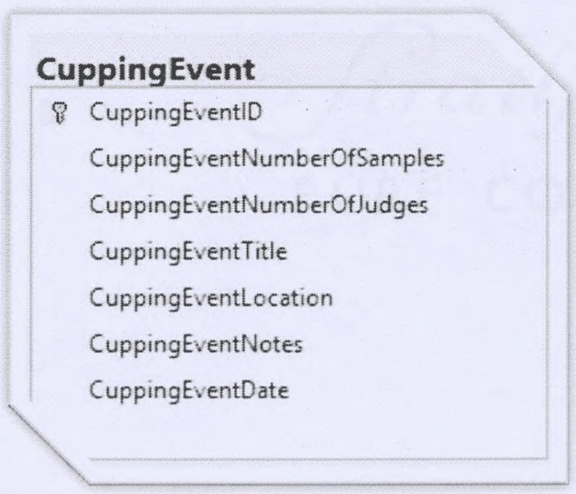
The AI Cupper client application targets the input of testing cupping events' data only. A cupping event is a combination of a set of coffee samples to be judged by a group of cuppers. To make the application complete, an administrative user interface module could be built to manage the creation, edition and deleting of these cupping events and their data through the AI Cupper Restful API.

In addition, the AI Cupper Restful API was built to be a key element of an enterprise integration strategy playing the role of a message oriented middleware (MOM) in an enterprise service bus (ESB). By taken this approach, the AI Cupper could evolve into a messaging broker. The AI Cupper could become the core of a communication infrastructure to loosely coupled support cupping events.

Appendix A

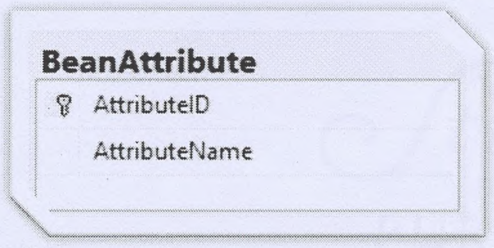
List of Domain Models. Each one of the following entities represents a database table matching objects used by the AI Cupper Restful API.

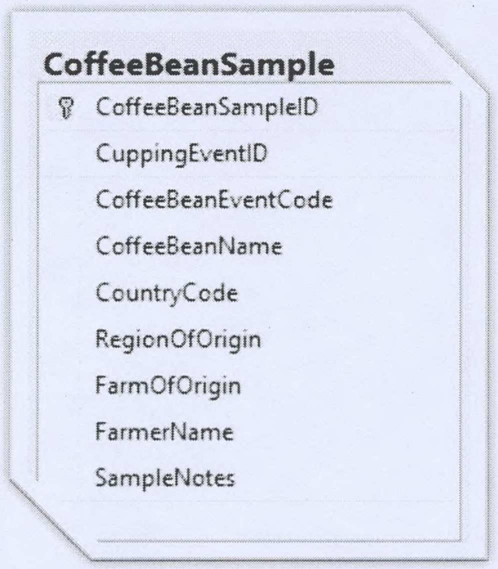
Entity Name	Description
Bean Attribute	Lookup table holding the list of coffee bean attributes
Country	Lookup table of the list of country coffee producers
Cupping Event	Contains all AI.CUPPER cupping events
Judge	Holds list if cuppers per cupping event
Coffee Bean Sample	List of Coffee Beans to be judged or cup per cupping event
Cupping Event Given Score	Break down of coffee bean attribute per sample on a given cupping event
Cupping Event Given Defect	Break down of the defects per sample on a given cupping event
Fuzzy Rule	List of all the AI.CUPPER Fuzzy Propositions
Cupping Event Inferred Quality Grading Score	Holds the output of the Mamdani-style reasoning engine for the given coffee beans of a particular cupping event




CuppingEventInferredQualityGradingScore
CuppingEventID
CoffeeBeanSampleID
CuppingEventInferredQualityGradingScoreId
InferredScored
FuzzyRule
FuzzyRuleID
FuzzyRuleText
FuzzyRuleDomainObject
FuzzyProposionType
LexerLog
IsActive
Country
CountryCode
CountryName


Judge
JudgeID
CuppingEventID
JudgeEventCode
JudgeName
EmailAddress
PhoneNumber


BeanAttribute
AttributeID
AttributeName


CoffeeBeanSample
CoffeeBeanSampleID
CuppingEventID
CoffeeBeanEventCode
CoffeeBeanName
CountryCode
RegionOfOrigin
FarmOfOrigin
FarmerName
SampleNotes


CuppingEventGivenScore
CuppingEventGivenScoreID
CuppingEventID
JudgeID
CuppingBeanSampleID
AttributeID
GivenScore


CuppingEventGivenDefect
CuppingEventDefectID
CuppingEventID
JudgeID
CuppingBeanSampleID
AttributeID
NumberOfCups
Intensity

Appendix B

List of Some of the Generated Fuzzy Rules

if fragrance is high and flavor is high and aftertaste is medium and acidity is medium and body is medium and balance is medium and overall is veryhigh then grading is excellent

if fragrance is high and flavor is veryhigh and aftertaste is medium and acidity is high and body is medium and balance is low and overall is veryhigh then grading is excellent

if fragrance is low and flavor is medium and aftertaste is medium and acidity is medium and body is medium and balance is medium and overall is medium then grading is excellent

if fragrance is low and flavor is medium and aftertaste is medium and acidity is veryhigh and body is low and balance is medium and overall is medium then grading is verygood

if fragrance is low and flavor is veryhigh and aftertaste is veryhigh and acidity is medium and body is medium and balance is veryhigh and overall is veryhigh then grading is excellent

if fragrance is medium and flavor is high and aftertaste is high and acidity is high and body is medium and balance is medium and overall is medium then grading is excellent

if fragrance is medium and flavor is high and aftertaste is high and acidity is medium and body is medium and balance is high and overall is medium then grading is excellent

if fragrance is medium and flavor is high and aftertaste is medium and acidity is high and body is high and balance is medium and overall is high then grading is excellent

if fragrance is medium and flavor is low and aftertaste is low and acidity is low and body is medium and balance is medium and overall is low then grading is good

if fragrance is medium and flavor is low and aftertaste is low and acidity is medium and body is medium and balance is low and overall is low then grading is good

if fragrance is medium and flavor is low and aftertaste is low and acidity is medium and body is medium and balance is medium and overall is low then grading is verygood

if fragrance is medium and flavor is low and aftertaste is low and acidity is medium and body is medium and balance is medium and overall is medium then grading is verygood

if fragrance is medium and flavor is low and aftertaste is medium and acidity is low and body is medium and balance is medium and overall is medium then grading is verygood

if fragrance is medium and flavor is low and aftertaste is medium and acidity is medium and body is medium and balance is medium and overall is medium then grading is excellent

if fragrance is medium and flavor is low and aftertaste is medium and acidity is medium and body is medium and balance is medium and overall is medium then grading is verygood

if fragrance is medium and flavor is medium and aftertaste is high and acidity is medium and body is high and balance is medium and overall is medium then grading is excellent

if fragrance is medium and flavor is medium and aftertaste is low and acidity is low and body is medium and balance is medium and overall is medium then grading is excellent

if fragrance is medium and flavor is medium and aftertaste is medium and acidity is high and body is medium and balance is high and overall is veryhigh then grading is excellent

if fragrance is medium and flavor is medium and aftertaste is medium and acidity is high and body is medium and balance is medium and overall is medium then grading is excellent

if fragrance is medium and flavor is medium and aftertaste is medium and acidity is high and body is medium and balance is medium and overall is medium then grading is verygood

if fragrance is medium and flavor is medium and aftertaste is medium and acidity is high and body is medium and balance is veryhigh and overall is high then grading is excellent

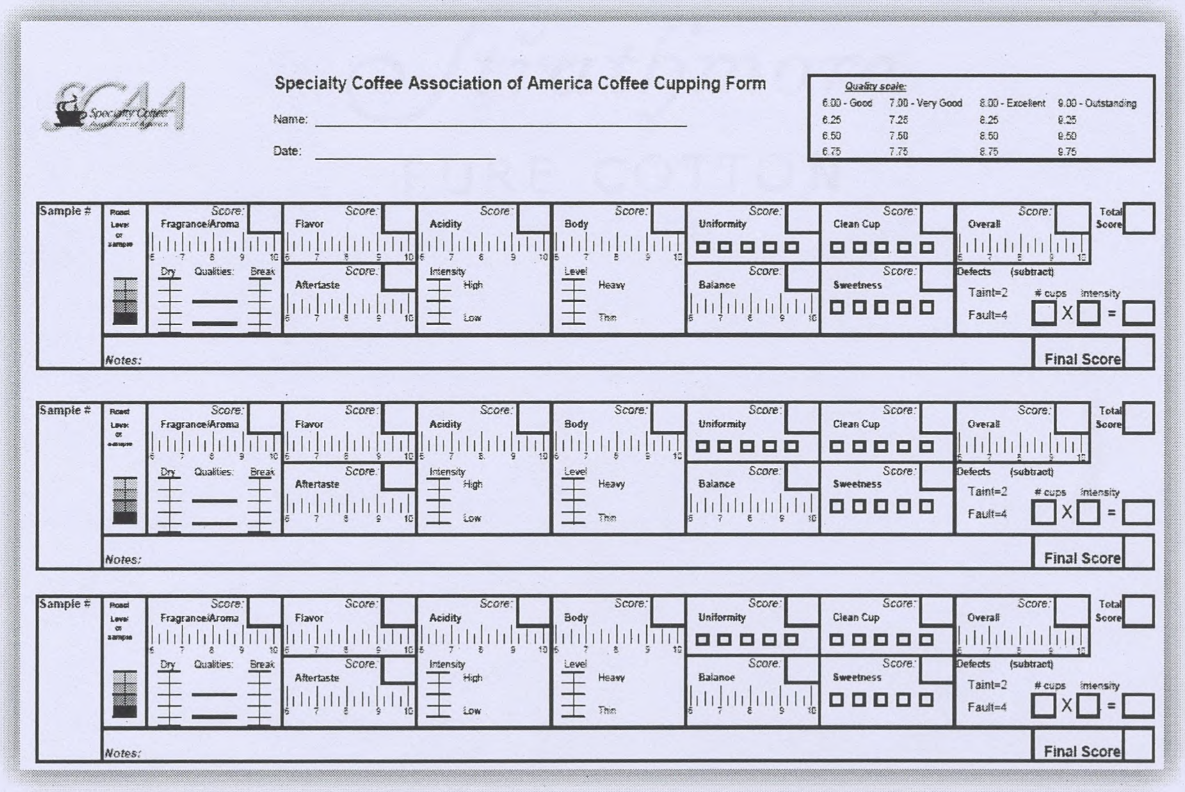
if fragrance is medium and flavor is medium and aftertaste is medium and acidity is medium and body is high and balance is medium and overall is high then grading is excellent

if fragrance is medium and flavor is medium and aftertaste is medium and acidity is medium and body is medium and balance is high and overall is high then grading is excellent

if fragrance is medium and flavor is medium and aftertaste is medium and acidity is medium and body is medium and balance is high and overall is medium then grading is excellent

Appendix C

Specialty Coffee Association of America (SCAA) Cupping Form



Specialty Coffee Association of America Coffee Cupping Form

Name: ______________________

Date: ______________

Quality scale:			
6.00 - Good	7.00 - Very Good	8.00 - Excellent	9.00 - Outstanding
6.25	7.25	8.25	9.25
6.50	7.50	8.50	9.50
6.75	7.75	8.75	9.75

Sample # | Roast Level of sample | Fragrance/Aroma Score: (Dry, Qualities:, Break) | Flavor Score: | Aftertaste Score: | Acidity Score: (Intensity: High, Low) | Body Score: (Level: Heavy, Thin) | Uniformity Score: | Balance Score: | Clean Cup Score: | Sweetness Score: | Overall Score: | Defects (subtract) Taint=2, Fault=4, # cups X Intensity = | Total Score

Notes: | Final Score

Sample # | Roast Level of sample | Fragrance/Aroma Score: (Dry, Qualities:, Break) | Flavor Score: | Aftertaste Score: | Acidity Score: (Intensity: High, Low) | Body Score: (Level: Heavy, Thin) | Uniformity Score: | Balance Score: | Clean Cup Score: | Sweetness Score: | Overall Score: | Defects (subtract) Taint=2, Fault=4, # cups X Intensity = | Total Score

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Sample # | Roast Level of sample | Fragrance/Aroma Score: (Dry, Qualities:, Break) | Flavor Score: | Aftertaste Score: | Acidity Score: (Intensity: High, Low) | Body Score: (Level: Heavy, Thin) | Uniformity Score: | Balance Score: | Clean Cup Score: | Sweetness Score: | Overall Score: | Defects (subtract) Taint=2, Fault=4, # cups X Intensity = | Total Score

Notes: | Final Score

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[i] Allen Newell and Herbert Simon from Carnegie-Mellon University proposed a production system model, the foundation of the modern rule-based expert systems. They shared the 1975 Turing Award for their contributions to artificial intelligence, the psychology of human cognition, and list processing.